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CAPM-Based Company (Mis)valuations*

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Abstract

There is a discrepancy between CAPM-implied and realized returns. Using the CAPM in capital budgeting – as recommended in finance textbooks – should thus have valuation effects. For instance, low beta projects should be valued more by CAPM-using managers than by the market. This paper empirically tests this hypothesis using publicly announced M&A decisions and shows that takeovers of lower beta targets are accompanied by lower cumulative abnormal returns for the bidders. Specifically, our estimates imply an average net loss to bidders corresponding to 12% of the average deal value and exceeding USD 10 billion per year in aggregate.

JEL Classification: G31, G34, G41

Keywords: Capital Budgeting, Valuation, Mergers and Acquisitions, Capital Asset Pricing Model

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1 Introduction

The Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966) is the predominant model of risk and return taught by academics in universities and business schools in undergraduate, MBA, and executive education programs. The CAPM is also widely used in practice, in particular, to estimate firms' cost of (equity) capital.[1] However, it is well known that the CAPM does not fit the data. The average realized returns of low beta securities are higher and those of high beta securities lower than the CAPM predicts. In other words, the slope of the empirical security market line (SML) is less steep than implied by the CAPM (e.g., Black, Jensen, and Scholes, 1972; Fama and French, 2004; Baker, Bradley, and Wurgler, 2011; Frazzini and Pedersen, 2014).

We show that the widespread use of the CAPM for cost of capital estimations despite the divergence between CAPM-implied and realized returns has important implications for the market's reaction to firms' capital budgeting decisions. The intuition is as follows. For low beta investments, the cost of capital implied by the CAPM is lower than the cost of capital implied by the empirical SML. Equivalently, the "CAPM-based valuation" of low beta investments exceeds their market valuation. As a consequence, managers who rely on the CAPM for capital budgeting purposes are willing to acquire low beta projects at prices that the market deems too high. The reverse holds for high beta projects. It follows that the stock market reaction upon the announcement of low beta investments is less favorable than upon the announcement of high beta investments.

[1] Among the CFOs of public firms surveyed in Graham and Harvey (2001, p. 201), "the CAPM is by far the most popular method of estimating the cost of equity capital: 73.5% of respondents always or almost always use the CAPM." Jacobs and Shivdasani (2012, p. 120) report that "about 90% of the respondents in a survey conducted by the Association for Financial Professionals use the capital asset pricing model (CAPM) to estimate the cost of equity." In a survey among valuation professionals, Mukhlynina and Nyborg (2016, p. 22) find that "76% of respondents use the CAPM almost always or always" to compute the cost of equity.

To test this prediction, we focus on large-scale investments: mergers and acquisitions. Using data from SDC Platinum for the period from 1977 to 2015, we show that takeover bids for low beta targets entail more negative stock market reactions than bids for high beta targets. Specifically, we find that a difference in target betas of one interquartile range is associated with a difference in bidder cumulative abnormal returns (CARs) of 0.5 to 1.2 percentage points, corresponding to 6% to 16% of the interquartile range of bidder CARs. This relation is not explained by any of the CAR determinants that have been documented in the existing literature and does not depend on the model we use to estimate betas or CARs. We also do not find any evidence of return reversal in the long run, suggesting long-lasting wealth effects for investors. To the best of our knowledge, we are the first to document this relation between bidder CARs and target betas. In terms of dollar values, our estimates imply that acquirers incur an average loss per deal of USD 37 million due to their reliance on the CAPM. This loss corresponds to 12% of the average deal value and implies aggregate losses in excess of USD 10 billion per year.

Potential concerns are that our estimates of target betas may only be noisy proxies for the actual beta-estimates used by managers or that target betas may be correlated with unobserved determinants of bidder CARs. For example, acquisitions of high beta targets may be associated with larger synergies, or high beta targets may have lower bargaining power vis-à-vis their acquirers. We mitigate such concerns by estimating two-stage-least-squares (2SLS) regressions. To do so, we rely on mutual fund fire sales as a source of non-fundamental variation in realized stock returns (i.e., noise), which in turn translates into non-fundamental variation in beta-estimates (i.e., noise in the coefficient estimates from a regression of excess stock on excess market returns). Using the (scaled) in-sample covariance between the estimated noise components of realized excess returns and excess market returns as an instrument for the beta-estimates corroborates our results: We find a positive and statistically significant relation between bidder CARs and target betas with a magnitude that is similar to our OLS estimates. We also show that high beta targets have lower bid-implied valuations, that betas do not predict future cash flows, and that there is no relation between target betas and the *combined* CARs of bidders and targets. All of these findings are at odds with the idea that acquisitions of high beta targets are associated with larger synergies. Further, we show that the WACC used in fairness opinions on the takeover bids increases with the targets' beta, supporting the premise that the CAPM is used to estimate discount rates in practice.

We also test a number of cross-sectional predictions. The positive relation between a bidder's CAR and target's beta is stronger if the target's relative size vis-à-vis the bidder and the target's growth rate are high. The intuition is that a larger size and higher growth rate amplify the difference between the CAPM-implied value of the target and the market's assessment of the target's value. We also find that the relation is stronger for bidders that are more likely to rely on the CAPM (as proxied by their mentioning of the CAPM in SEC filings). Consistent with the intuition that readily available market prices dampen the impact of using the CAPM for valuation purposes, we find that the relation between a bidder's CAR and target's beta is stronger for private than for public targets. Further, as bids below the current market price are unlikely to be accepted by the target's shareholders, we predict and find that the relation between a bidder's CAR and target's beta vanishes for high beta public targets (but not for high beta private targets). These cross-sectional patterns are important as they lend further support to the idea that the positive relation between target betas and bidder CARs is indeed due to bidders' reliance on the CAPM despite the divergence between CAPM-implied and realized returns. Any alternative story must explain not only this main finding but also all of the cross-sectional results.

Bidders' reliance on the CAPM for valuation purposes also has implications for their choice between stock and cash offers. If bidders rely on the CAPM to assess the true value of their own equity, low (high) beta bidders will tend to perceive their own shares as undervalued (overvalued) by the market. We thus predict that low (high) beta bidders are less (more) likely to propose payment in stock. We find that this is indeed the case.

Finally, we explore the implications of relying on the CAPM for capital structure decisions. Similar to our prediction regarding the relation between a bidder's beta and the propensity to offer stock rather than cash when making a takeover bid, we predict that high beta firms are less likely to repurchase shares but more likely to issue equity than low beta firms. The intuition is that firms that believe to be overvalued by the market are more likely to issue equity and less likely to repurchase shares (Baker and Wurgler, 2013; Graham and Harvey, 2001; Brav, Graham, Harvey, and Michaely, 2005). Our analyses provide strong support for this prediction.

Our paper's contribution is to show that the widespread use of the CAPM for capital budgeting and valuation purposes in practice despite the well known divergence between CAPM-implied and realized returns has real consequences. Firms that rely on the CAPM tend to overvalue low and undervalue high beta investment projects – relative to the market's assessment of the projects' value. From the market's point of view, these firms are thus prone to overpay for low beta projects and to acquire high beta projects at a bargain. As a consequence, the market tends to react negatively (positively) to the announcement of new low (high) beta projects. Moreover, firms' reliance on the CAPM has implications for their capital structure decisions. Low beta firms are more likely to perceive their own stock as undervalued by the market and are thus less likely to issue equity and more likely to repurchase shares. The opposite holds for high beta firms.

Our work is related to recent literature on the real effects of the use or misuse of the CAPM in corporate finance. Most related is Baker, Hoeyer, and Wurgler (2016), who start from the same observation as we do: High beta stocks have low realized returns. As a result, CAPM-using managers believe high beta equity to be overvalued by the market. Hence, high beta firms tend to use more equity and less debt. Baker, Hoeyer, and Wurgler (2016) assume that CAPM-using managers are right and maximize shareholder value. But their theory is also consistent with CAPM-using managers being wrong but believing they maximize shareholder value. In any case, the discrepancy between CAPM-implied and realized returns has, in their paper, a real effect on leverage. In our paper, we focus on the valuation effect of the discrepancy, though we confirm their capital structure results in our analysis of stock issuances and repurchases (Section 4.7). Jagannathan, Matsa, Meier, and Tarhan (2016) offer survey evidence that high beta firms use higher discount rates than low beta firms, which supports the premise that firms use the CAPM to compute discount rates. Our paper is further related to Krüger, Landier, and Thesmar (2015), who also assume that firms use the CAPM in valuation but tend to apply the beta of the firm's core division even to projects with a different risk level. Hence, while we expect high beta targets to be undervalued, Krüger, Landier, and Thesmar (2015) expect targets acquired by high beta bidders to be undervalued. These are two different mechanisms, but to make sure our findings are not driven by bidders using their own cost of capital to value targets, we check that our results are unchanged when controlling for the bidder's beta. Our paper is also related to Levi and Welch (2016), who recommend that betas be computed with a double shrinkage. This would be consistent with an interpretation of our results whereby managers overestimate the slope of the real SML. Finally, our paper is related to van Binsbergen and Opp (2017)'s recent study on the quantitative impact of real anomalies. They explore a wider set of anomalies than we do but perform a very different exercise from ours: They make a model-based quantification of the real impact of anomalies, while we attempt to trace out the impact of one anomaly on firm behavior in the data.

The paper proceeds as follows. In Section 2, we develop our main predictions. In Section 3, we describe the data, and in Section 4, we present the empirical results. We address potential alternative explanations in Section 5. We discuss possible interpretations of our finding (are managers irrational or not?) and provide suggestive evidence in Section 6. We conclude in Section 7. The appendix contains variable definitions, robustness tests, and extensions.

2 Predictions

To provide a framework for our analysis, we now introduce a simple model that formalizes our arguments. We consider a public firm that offers to acquire a fraction $\pi \in [0,1]$ of another firm's equity at a price $B_t \equiv \pi \times E_t$, where E_t is the value of the target's equity as assessed by the bidder.[2] We denote with E_t^{Bidder} the market value of the bidder's equity, with $\widetilde{E}_t$ the value of the target's equity as assessed by the market, and with ρ the market's assessment of the probability that the bid will be accepted. The cumulative abnormal return of the bidder's stock in response to the bid announcement is given by[3]

$$CAR_t^{Bidder} = \frac{\rho \times \pi}{E_t^{Bidder}} \times \left(\widetilde{E}_t - E_t \right). \tag{1}$$

Going forward, we assume for simplicity that the target is unlevered and that its future expected free cash flows (FCF_{t+1}) grow at a constant rate g that is smaller than the cost of capital but larger than the risk-free rate.[4] The bidder computes the value of the target (including any potential synergies) by discounting the expected free cash flows at the cost of capital implied by the CAPM,

$$r_A = r_f + \beta_A \times \mu, \tag{2}$$

where r_f denotes the risk-free rate, β_A the bidder's estimate of the target's asset beta, and μ the market risk premium. Hence, the bidder's assessment of the target's value is

$$E_t = \frac{FCF_{t+1}}{r_A - g} = \frac{FCF_{t+1}}{r_f + \beta_A \times \mu - g}. \tag{3}$$

[2]Assuming that the bidder offers $B_t = \pi \times E_t$ facilitates the analysis but is not crucial. Our predictions are qualitatively unchanged for any $B_t = B_t(\pi, E_t)$ with $\frac{\partial B_t(\pi, E_t)}{\partial E_t} > 0$.

[3]We assume that any gains or losses in case the bid is accepted are absorbed by the bidder's shareholders (rather than its creditors) and that there is no effect on the market value of the bidder's equity in case the bid is not accepted.

[4]We show in the appendix that considering a levered target does not (qualitatively) change our predictions.

Note that the assumption that the bidder relies exclusively on a discounted cash flow (DCF) analysis to value the target is for ease of exposition only. Assuming that the bidder values the target also based on multiples (that are independent of β_A) does not qualitatively change our predictions as long as the bidder places at least some weight on the DCF-implied value.

Unlike the bidder (who relies on the CAPM), the market values the target based on the cost of capital $\widetilde{r}_A$ that is implied by the empirical security market line (SML). For simplicity, we assume that the empirical SML is flat and crosses the CAPM-implied SML at $\beta = 1$.[5] As a consequence, the market's assessment of the target's value is

$$\widetilde{E}_t = \frac{FCF_{t+1}}{\widetilde{r}_A - g} = \frac{FCF_{t+1}}{r_f + \mu - g}. \tag{4}$$

The bidder's cumulative abnormal return around the bid announcement can thus be written as

$$CAR_t^{Bidder} = \frac{\rho \times \pi}{E_t^{Bidder}} \times \left(\frac{FCF_{t+1}}{r_f + \mu - g} - \frac{FCF_{t+1}}{r_f + \beta_A \times \mu - g} \right) = \frac{R \times \rho \times \mu \times (\beta_A - 1)}{r_f + \mu - g}, \tag{5}$$

where $R \equiv \pi \times E_t / E_t^{Bidder}$ denotes the relative size of the bid vis-à-vis the market value of the bidder's equity. Taking the partial derivative with respect to the target's asset beta, we obtain

$$\frac{\partial CAR_t^{Bidder}}{\partial \beta_A} = \frac{\rho \times \pi}{E_t^{Bidder}} \times \frac{\mu \times FCF_{t+1}}{(r_f + \beta_A \times \mu - g)^2} = \frac{R \times \rho \times \mu}{r_f + \beta_A \times \mu - g} > 0, \tag{6}$$

which motivates our main prediction:[6]

Prediction 1 *The bidder's cumulative abnormal return $\left(CAR_t^{Bidder}\right)$ around the bid announcement is increasing in the target's asset beta (β_A).*

[5] We analyze the case of an empirical SML that is merely less steep than the CAPM-implied SML in the appendix.

[6] When deriving equation (6), we implicitly assume $\partial \rho / \partial \beta_A = 0$. This can be motivated as follows. Suppose $\rho = \rho(\delta) + \epsilon$ with $\delta \equiv B_t - \pi \times E_t'$. E_t' denotes the target's value as assessed by its owners, and ϵ is a random term that is independent of everything else. That is, suppose the probability that the bid is accepted depends on the perceived attractiveness of the bid (δ) and some random component (ϵ). If the target's owners rely on the CAPM (just like the bidder does), we have $E_t' = E_t$, $\delta = 0$, and thus $\partial \rho / \partial \beta_A = 0$. Consistent with this argument, unreported empirical tests based on our sample of takeover bids fail to reject the null-hypothesis that $\partial \rho / \partial \beta_A = 0$.

Differentiating equation (6) with respect to the relative size of the bid (R) and the growth rate of the target's expected free cash flows (g) yields

$$\frac{\partial^2 CAR_t^{Bidder}}{\partial \beta_A \partial R} = \frac{\rho \times \mu}{r_f + \mu - g} > 0 \tag{7}$$

and

$$\frac{\partial^2 CAR_t^{Bidder}}{\partial \beta_A \partial g} = \frac{\rho \times \pi}{E_t^{Bidder}} \times \frac{2 \times \mu \times FCF_{t+1}}{\left(r_f + \beta_A \times \mu - g\right)^3} > 0, \tag{8}$$

which leads to the following cross-sectional predictions:

Prediction 2 *The positive relation between the bidder's cumulative abnormal return* $\left(CAR_t^{Bidder}\right)$ *around the bid announcement and the target's asset beta* (β_A) *is stronger if*

a) the relative size of the bid (R) *is larger.*

b) the growth rate of the target's expected free cash flows (g) *is larger.*

3 Data

Data on takeover bids come from Thomson Financial's SDC Platinum M&A database. We use all observations between 1977 and 2015 with a public bidder and a deal value of at least USD 50 million (inflation adjusted to December 2015 terms). Table 1 presents descriptive statistics.[7] We distinguish between bids for private targets (Panel A) and bids for public targets (Panel B).

[Table 1 around here.]

The average cumulative abnormal return of the bidders' stock around the bid announcements (from $t = -3$ to $t = +3$ for a bid announced on date $t = 0$) is positive for private targets (2.0%) and negative for public targets (-0.6%), consistent with the existing literature (e.g., Betton, Eckbo, and

[7] All continuous variables are winsorized at the 1st and 99th percentile. Definitions are provided in the appendix.

Thorburn, 2008; Schneider and Spalt, 2017). The average deal value is USD 388 million (inflation-adjusted) for private and USD 1,258 million for public targets. Bidders offer an all-stock payment in 13% (33%) of the cases if the target is private (public). The average WACC used to provide fairness opinions on the proposed deals is 14.1% for private and 13.1% for public targets.

The private (public) targets in our sample have an average asset beta of 0.86 (0.82) with a standard deviation of 0.33 (0.36). The distribution of asset betas for the bidders is very similar. All betas are computed as follows: First, for each public firm i in CRSP and at the end of each month t, we regress monthly excess stock returns (RET in CRSP minus the risk-free rate from Kenneth French's webpage[8]) during the previous five years – i.e., from month $t-60$ to month t – on the corresponding excess returns of the CRSP value-weighted portfolio (including dividends). The regression coefficient is the CAPM (equity-)beta β_{it}^{E}.[9] To ensure reasonable precision, we drop estimates based on less than 36 months of return data. Further, we drop observations for which the estimated beta is negative, and we drop the same number of observations in the right tail of the distribution of estimated betas. Second, we delever each beta using the formula $\beta_{it}^{A} = \beta_{it}^{E} / [1 + (1-\tau) \times D_{it}/E_{it}]$, where τ is the statutory tax rate in the highest bracket, D_{it} is total debt at the end of the most recently completed fiscal year ($DLT + DLC$ in Compustat), and E_{it} is the market capitalization of firm i at the end of month t. Using alternative methodologies to delever the equity betas does not materially affect the results. Third, we compute the equally weighted average of β_{it}^{A} of all public firms in CRSP with the same three-digit primary SIC code. Finally, we attribute to the target and the bidder the equally weighted average asset beta of their respective industries as of the last completed month before the bid announcement. Hence, if the bidder and the target operate in the same industry, they have the same asset beta.

[8] *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*

[9] We use sharecodes 10 and 11 and compute the value-weighted average beta in case of multiple securities per firm.

It is important to note that to test our predictions, we require an estimate of the beta that was used by the bidder when valuing the target. That is, our goal is not to estimate a target's "true" CAPM-beta but to replicate as closely as possible the estimation procedure most likely used by a bidder in our sample. For that reason, we follow common industry practice and rely on five years of monthly returns, use the standard (textbook) formula to delever equity betas, and compute the equally weighted average asset beta of the target's public peers. Our results, however, are not materially affected when using alternative methodologies to estimate, delever, or aggregate betas.

4 Results

4.1 Cumulative Abnormal Returns of Bidders' Stock

We now test our main prediction: The bidder's cumulative abnormal return around the bid announcement is increasing in the target's asset beta (Prediction 1). For the purpose of this analysis, we focus on takeover bids for private targets. The reason is that we expect the relation between a bidder's CAR and target's asset beta to be weaker for public targets. The intuition is as follows.

For public targets, the market's valuation is observable in form of the targets' market capitalization. This has two consequences. First, we expect the observable market valuation to act as a counterweight to the bidders' own assessment of the targets' value: Bidders are likely to adjust their own valuations downward (upward) if they exceed (fall short of) the market's valuation. Second, bidders are unlikely to successfully acquire public targets at prices below their current market capitalizations because the targets' shareholders are unlikely to accept such offers. As a consequence, we do not expect to find a relation between bidders' announcement CARs and targets' asset betas for high beta public targets (whose market value is likely to exceed the CAPM-implied value). For this reason, we restrict attention to private targets. We test our model's differential predictions regarding private and public targets in section 4.5.

We estimate the following OLS regression:

$$\begin{aligned} \textit{Bidder CAR} &= \alpha + \beta \times \textit{Target Asset Beta} + \gamma \times \textit{Beta Spread} \\ &+ \delta' \textit{Deal Controls} + \eta' \textit{Target Controls} + \kappa' \textit{Bidder Controls} \\ &+ \textit{Bidder Industry} \times \textit{ Year Fixed Effects} + \varepsilon. \end{aligned} \tag{9}$$

Bidder CAR is the bidder's cumulative abnormal return during the seven days around the bid announcement (i.e., from date $t-3$ to date $t+3$ for a bid announced on date $t = 0$).[10] *Target Asset Beta* is the target's asset beta. *Beta Spread* is the difference between the target's and bidder's asset beta. We include this variable to control for the effect of bidders using their own beta – rather than the target's beta – to compute the cost of capital (Krüger, Landier, and Thesmar, 2015). *Deal Controls* are characteristics that are commonly used as control variables in the M&A literature.[11] *Target Controls* are the target's market-to-book ratio, return on assets, and leverage, as well as cash holdings and cash flow (both scaled by assets).[12] *Bidder Controls* are defined analogously. The standard errors are clustered by target industry.[13]

[Table 2 around here.]

Table 2 presents the results. In column (1), we do not include any control variables other than

[10]Our findings are robust to using alternative event windows, e.g., from $t-2$ to $t+2$ or from $t-1$ to $t+1$.

[11]See, e.g., Moeller, Schlingemann, and Stulz (2004), Masulis, Wang, and Xie (2007), Golubov, Petmezas, and Travlos (2012), Harford, Humphery-Jenner, and Powell (2012), and Dessaint, Golubov, and Volpin (2017). Specifically, we control for *Deal Value (Log)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same Industry*, *Crossborder*, *Poison*, *Tender*, *Multiple Bidders*, *Relative Size*, and *Bidder Size (Log)*. Detailed definitions are provided in the appendix.

[12]For private firms, we use the equally weighted average of these variables computed across all public firms that operate in the same industry (based on the first three digits of the firms' primary SIC code).

[13]Our findings are unchanged if we use block bootstrap standard errors instead.

the fixed effects. We add the deal controls in column (2), the target controls in column (3), and the bidder controls in column (4). In column (5), we also add *Beta Spread*, the difference between the target's and the bidder's asset beta. To conserve space, we do not report the coefficient estimates and associated t-statistics for the target and bidder controls.

In all five columns, we find positive coefficient estimates on *Target Asset Beta* that are statistically significant at the 1% level.[14] The point estimates range from 1.02 in column (1) to 2.55 in column (5) and imply that an increase in *Target Asset Beta* by one interquartile range (0.49) is associated with an increase in *Bidder CAR* by 0.5 to 1.2 percentage points, corresponding to 6% to 16% of *Bidder CAR*'s interquartile range (7.9%).

4.2 Instrumental Variable Estimation

Potential concerns are that the variable *Target Asset Beta* may only be a noisy proxy for the actual beta-estimate used by managers or that *Target Asset Beta* may be correlated with unobserved determinants of bidder CARs (e.g., synergies or bargaining power). In the former case, our estimates would suffer from an attenuation bias and underestimate the true relation between bidder CARs and target betas (as estimated by the bidders). In the latter case, our estimates could be either upward- or downward-biased, depending on the signs of the correlations between the unobserved determinants, *Target Asset Beta*, and bidder CARs.

To address such concerns, we construct an instrument for *Target Asset Beta* and estimate the effect on bidder CARs in a two-stage-least-squares (2SLS) framework. To do so, we rely on mutual fund fire sales as a source of non-fundamental variation in realized stock returns (i.e., noise), which in turn translates into non-fundamental variation in beta-estimates (i.e., noise in the coefficient

[14] Table A.1 in the appendix shows that this finding does not depend on the model used to estimate *Bidder CAR*. Table A.2 shows that the results are similar when we use the target's equity beta instead of its asset beta.

estimates from a regression of excess stock on excess market returns). The intuition is as follows.

In practice, a given firm's equity-beta is typically estimated by regressing realized stock returns in excess of a proxy for the risk free rate on realized excess returns of a market proxy. The beta-estimate is then defined as

$$\widehat{\beta} \equiv \frac{\widehat{\sigma}_{r,m}}{\widehat{\sigma}_m^2}, \tag{10}$$

where $\widehat{\sigma}_{r,m}$ denotes the in-sample covariance between the excess stock return r and the excess market return r_m, and $\widehat{\sigma}_m^2$ denotes the in-sample variance of r_m.[15]

The realized excess stock return can be written without loss of generality as the sum of a fundamental and a noise component,

$$r = r^* + u, \tag{11}$$

where r^* denotes the fundamental component, and the noise component is defined as $u \equiv r - r^*$. It follows that the beta-estimate ($\widehat{\beta}$) can be decomposed into a "fundamental beta" ($\widehat{\beta}^*$) and a "noise beta" ($\widehat{\beta}_u$), i.e.,

$$\widehat{\beta} = \frac{\widehat{\sigma}_{r,m}}{\widehat{\sigma}_m^2} = \frac{\widehat{\sigma}_{r^*,m}}{\widehat{\sigma}_m^2} + \frac{\widehat{\sigma}_{u,m}}{\widehat{\sigma}_m^2} = \widehat{\beta}^* + \widehat{\beta}_u, \tag{12}$$

where $\widehat{\sigma}_{r^*,m}$ and $\widehat{\sigma}_{u,m}$ are the in-sample covariances between r^* and r_m and u and r_m, respectively. This decomposition suggests that the (scaled) in-sample covariance between non-fundamental shocks to a firm's realized excess stock returns and the excess returns on the market proxy can be used as an instrument for the beta-estimate, i.e., $\widehat{\beta}_u$ can be used to instrument $\widehat{\beta}$.

To implement this strategy, we rely on mutual fund fire sales as a source of non-fundamental variation in firms' realized stock returns. Coval and Stafford (2007) show that stock sales by mutual funds that experience large outflows create large, negative demand shocks for the liquidated

[15] Some data providers (e.g., Bloomberg) also offer "adjusted beta" estimates that are a weighted average between the "raw beta" estimate and one (e.g., $\widehat{\beta}_{adj.} = \frac{2}{3} \times \widehat{\beta} + \frac{1}{3}$). We abstract away from such adjustments as they complicate the exposition but do not change the intuition behind our identification strategy.

stocks and thus have a negative impact on realized returns. Fund managers, however, can exercise discretion when deciding which of their positions to liquidate. To mitigate the concern that fund managers' choices which shares to sell introduce a correlation between stock sales and firm fundamentals, we follow Edmans, Goldstein, and Jiang (2012) and rely on hypothetical rather than actual sales. In particular, for each stock, we compute the total dollar amount of hypothetical mutual fund fire sales scaled by the total dollar amount of trading in the stock (*HMFFS*), assuming that each position in an affected fund's portfolio is liquidated in proportion to its portfolio weight, so that the overall composition of the portfolio remains unchanged.[16] This approach ensures that the variable *HMFFS* is not affected by fund managers' discretion regarding which stocks to sell after a large outflow.

Next, we use *HMFFS* to estimate the non-fundamental noise component in firms' stock returns. Specifically, for each public firm in the CRSP database and for each beta-estimation period in our sample, we regress the firm's realized excess stock return r on *HMFFS*,

$$r = \alpha + \gamma \times HMFFS + \varepsilon, \tag{13}$$

and use the fitted value from this regression – the predicted excess return due to mutual fund fire sales – as an estimate of the non-fundamental noise component ($\widehat{u}$) in the realized excess return.[17]

We then define

$$\widehat{\beta}_{\widehat{u}} \equiv \frac{\widehat{\sigma}_{\widehat{u},m}}{\widehat{\sigma}_m^2}, \tag{14}$$

where $\widehat{\sigma}_{\widehat{u},m}$ is the in-sample covariance between the estimated noise component and the realized excess return of the market proxy. Finally, in analogy to the construction of *Target Asset Beta*, we

[16] We provide a detailed description of the construction of *HMFFS* in the appendix.

[17] Note that our approach does not require that *HMFFS* explains the entire noise term u in $r = r^* + u$. In particular, assume that u is the sum of unexplained noise η and noise ν that is due to mutual fund fire sales, i.e., $r = r^* + \eta + \nu$. In that case, we have $\widehat{\beta} = \widehat{\beta}^* + \widehat{\beta}_\eta + \widehat{\beta}_\nu$, and $\widehat{\beta}_\nu$ can be used to instrument $\widehat{\beta}$.

delever the firm-level estimates of $\widehat{\beta}_u$ and compute the equally-weighted average at the industry level. The resulting variable – denoted *Target Noise Beta* – is our instrument for *Target Asset Beta*.[18]

To be a valid instrument, *Target Noise Beta* must satisfy two conditions. First, it must be correlated with *Target Asset Beta*. This condition can be tested using the first-stage of the 2SLS procedure: The results show that the correlation between *Target Noise Beta* and *Target Asset Beta* is positive and highly statistically significant (Table 3, Panel A). With t-statistics above ten, the implied F-statistics are an order of magnitude larger than the threshold suggested by Stock, Wright, and Yogo (2002) to guard against weak instruments. To mitigate concerns about the robustness of this finding, we explore the correlation between the two variables in further detail. Figure A.1 (in the appendix) shows the estimated coefficients from a regression of *Target Asset Beta* on indicator variables for different ranges of *Target Noise Beta*. This analysis reveals a strong and monotone relation that corroborates the positive correlation between *Target Asset Beta* and *Target Noise Beta* that we find in Table 3, Panel A.

The second condition that *Target Noise Beta* must satisfy to be a valid instrument is that it must be uncorrelated with the error term in the regression of *Bidder CAR* on *Target Asset Beta*. This condition cannot be tested. Note, however, that $\widehat{\beta}_{\widehat{u}}$ is the (scaled) in-sample covariance between the estimated noise component in realized excess stock returns and realized excess returns on the market proxy. This implies that *Target Noise Beta* is as good as randomly assigned as long as the estimated effect of mutual fund fire sales on excess stock returns indeed represents non-fundamental noise. The evidence documented in a growing number of papers is consistent with this premise:

[18] To ensure that *Target Noise Beta* and *Target Asset Beta* are constructed based on the same sample of observations, we exclude $\widehat{\beta}_u$-estimates if the corresponding $\widehat{\beta}$-estimates are missing. Further, we set *Target Noise Beta* to missing if the average estimated effect of *HMFFS* on r at the industry level is in the top or bottom percentile of the sample distribution. This procedure mitigates the concern that *Target Noise Beta* may be driven by outliers in the distribution of estimated noise components.

Mutual fund fire sales trigger a drop in stock prices that is followed by subsequent reversal, and corporate insiders trade against these shocks.[19] Both findings are consistent with the notion that mutual fund fire sales represent temporary, non-fundamental demand shocks that induce noise in firms' stock returns.[20]

Finally, it is unclear why the in-sample covariance between non-fundamental noise in the return realizations and the excess market return during the beta-estimation period (i.e., during the five years before the deal announcement) would affect the bidder CAR in a subsequent acquisition through any channel other than the effect on the beta estimate. Taken together, plausibly random assignment of $\widehat{\beta}_{\widehat{u}}$ and a single channel – the effect on $\widehat{\beta}$ – through which $\widehat{\beta}_{\widehat{u}}$ affects bidder CARs suggest that *Target Noise Beta* is uncorrelated with the error term in the regression of *Bidder CAR* on *Target Asset Beta* and thus satisfies the exclusion restriction.

Table 3 displays the results of the 2SLS estimation.[21] In Panel A, columns (1) to (4), we present the results of the first-stage regressions of *Target Asset Beta* on *Target Noise Beta*. In columns (5.a) and (5.b), we instrument *Target Asset Beta* and *Beta Spread* with *Target Noise Beta* and *Bidder Noise Beta*.[22] The coefficient estimates on *Target Noise Beta* in all columns are positive and strongly significant. Similarly, the coefficient on *Bidder Noise Beta* in column (5.b) is negative and strongly significant.

In Panel B, we report the results of the second-stage regressions. The coefficient estimates on

[19]See, e.g., Ali, Wei, and Zhou (2011), Goldman (2017), Honkanen and Schmidt (2017), and Dessaint, Foucault, Frésard, and Matray (2018).

[20]Other papers that exploit mutual fund fire sales as a source of non-fundamental shocks to stock prices/returns include Edmans, Goldstein, and Jiang (2012), Phillips and Zhdanov (2013), Acharya, Almeida, Ippolito, and Perez (2014), and Eckbo, Makaew, and Thorburn (2017).

[21]The sample period for this analysis is 1980 to 2015 as data on mutual funds flows is not available prior to 1980.

[22]We construct *Bidder Noise Beta* in analogy to *Target Noise Beta*.

Target Asset Beta are positive and statistically significant in all five columns – at the 5% level in columns (1) to (3) and at the 10% level in columns (4) and (5). Further, the IV coefficient estimates are similar in magnitude to the OLS estimates presented in Table 2. These results corroborate our earlier findings of a positive relation between *Target Asset Beta* and *Bidder CAR*.

4.3 Cross-Sectional Variation

We now test Predictions 2 a) and b) regarding cross-sectional variation of the relation between a bidder's CAR and target's asset beta. To do so, we define two indicators: *High Growth* is equal to one if the growth rate of aggregate sales in the target's industry over the past three years is larger than the sample median. *High Relative Size* is equal to one if the relative size of the takeover bid vis-à-vis the market value of the bidder's equity is larger than the sample median.

In addition, we also define the indicator *CAPM Usage*, which is equal to one if the words "CAPM" or "Capital Asset Pricing Model" occur in the bidder's 10K, 10Q, and 8K filings during the three years prior to the bid announcement. The idea is that the relation between a bidder's CAR and target's asset beta stems from the bidder's reliance on the CAPM. Hence, we expect a stronger effect for bidders that are more likely to use the CAPM and attempt to proxy for this likelihood with the indicator *CAPM Usage*.

We estimate OLS regressions in which we interact *Target Asset Beta* with the indicators just described.[23] Table 4 presents the results. To conserve space, we do not report the coefficient estimates and corresponding t-statistics for the control variables.

[Table 4 around here.]

As predicted by our model, we find that the relation between a bidder's cumulative abnormal

[23]We also interact all control variables and fixed effects with these indicators, thus allowing their coefficients to depend on the values of *High Growth*, *High Relative Size*, and *CAPM Usage*, respectively.

return around the bid announcement and the target's asset beta is stronger if the growth in the target's industry is high and if the relative size of the bid is high. Further, the relation is stronger if the bidder is more likely to rely on the CAPM (as proxied by the indicator *CAPM Usage*).

4.4 Model Calibration and Implied Losses to Bidders

To assess how well our model explains the relation between *Bidder CAR* and *Target Asset Beta*, we calibrate the model to the data. For the purpose of this calibration, we allow for different degrees of steepness of the empirical SML. Specifically, we assume that the empirical SML has a slope of $\gamma \times \mu$ for some $\gamma \in [0, 1]$, so that the cumulative abnormal return of the bidder's stock in response to the bid announcement is given by[24]

$$CAR_t^{Bidder} = \rho \times \frac{\pi \times FCF_{t+1}}{E_t^{Bidder}} \times \left[\frac{1}{r_f + (\gamma \times \beta_A + 1 - \gamma) \times \mu - g} - \frac{1}{r_f + \beta_A \times \mu - g} \right]. \tag{15}$$

The average bid for private targets has a value of USD 314 million, and the average market value of the bidder's equity is USD 10,269 million. The average probability that a bid is accepted is 92%.[25] We use the average yield on 20-year U.S. treasury bonds during the sample period (5.0%) to proxy for the risk-free rate, the average nominal GDP growth (5.4%) to proxy for the growth rate of the target's expected free cash flows, and we assume a market risk premium of 6%. Using these values, we compute the model-implied bidder CAR given by equation (15) for different values of the target's asset beta and different degrees of steepness of the empirical SML.[26]

[Figure 1 around here.]

[24] See the appendix for the derivation. A flat empirical SML corresponds to $\gamma = 0$, and an empirical SML that coincides with the CAPM-implied SML corresponds to $\gamma = 1$.

[25] These statistics are based on the sample of 12,109 observations used to estimate column (5) in Table 2.

[26] We hold $\frac{\pi \times FCF_{t+1}}{E_t^{Bidder}} = \frac{B_t \times (r_A - g)}{E_t^{Bidder}}$ constant at $\frac{314 \times (0.05 + 0.9 \times 0.06 - 0.054)}{10{,}269} = 0.153\%$, based on our assumptions about the model parameters and an average target asset beta of 0.9 in the sample used to estimate column (5) of Table 2.

Figure 1 presents the results. The dashed blue line shows the model-implied bidder CAR for an empirical SML that is entirely flat ($\gamma = 0$) and the dashed gray line for an empirical SML that coincides with the SML implied by the CAPM ($\gamma = 1$). The solid blue line corresponds to the case of an empirical SML that is half as steep as the CAPM-implied SML ($\gamma = 0.5$). The solid red line shows the OLS coefficient estimates of indicator variables for different ranges of asset betas (using the same controls as in column (5) of Table 2).[27] Overall, except for very low asset betas, the model captures the empirical relation between *Bidder CAR* and *Target Asset Beta* reasonably well.

The calibration of our model also allows us to assess the implied dollar value of the losses incurred by the bidders that are due to their reliance on the CAPM. The idea is that we observe the bidders' actual bids and can use the calibrated model to back-out the counterfactual bids that would have been made had the bidders relied on the empirical SML when valuing the targets. We then estimate the implied loss to the bidders (Δ) as the difference between the actual bids (B_t) and the counterfactual bids ($\widetilde{B}_t$). Specifically, for each completed takeover, we compute[28]

$$\Delta \equiv B_t - \widetilde{B}_t = B_t \times \frac{\widetilde{r}_A - r_A}{\widetilde{r}_A - g} = B_t \times \frac{\mu \times (1 - \beta_A) \times (1 - \gamma)}{r_f + (\gamma \times \beta_A + 1 - \gamma) \times \mu - g}, \tag{16}$$

using the actual bid B_t that we observe in the data, our estimate of β_A for the target, $\gamma = 0.5$, $r_f = 5\%$, $\mu = 6\%$, and $g = 5.4\%$.

Based on this computation, we estimate a mean (median) implied loss of USD 37 million (USD 7 million) per completed deal, corresponding to 12% (6%) of the mean (median) deal value of USD 299 million (USD 111 million) for completed takeovers of private targets. To put these numbers in perspective, note that the mean (median) offer premium in control contests for public U.S. targets reported in Betton, Eckbo, and Thorburn (2008) is 48% (39%). Assuming implied offer premiums of a similar magnitude for private targets, our estimates imply that the loss per deal due to relying

[27] The corresponding coefficient estimates are reported in Table A.3 in the appendix.

[28] Note that our model implies $B_t = \pi \times \frac{FCF_{t+1}}{r_A - g}$ and $\widetilde{B}_t = \pi \times \frac{FCF_{t+1}}{\widetilde{r}_A - g}$.

on the CAPM corresponds to 25% (15%) of the mean (median) offer premium. Aggregating across all completed takeovers of private targets in our sample, our estimates imply a total loss of USD 427 billion incurred by the bidders between 1977 to 2015, thus exceeding USD 10 billion per year.

Our model implies that all losses incurred by the bidders are gains that accrue to the targets (and vice versa). Hence, an alternative perspective is to compute the absolute value of the difference between each actual and counterfactual bid ($|\Delta|$). Doing so allows us to gauge the magnitude of the wealth transfers between the bidders' and targets' shareholders – and thus the misallocation of capital – that is due to their reliance on the CAPM. The mean (median) value of $|\Delta|$ for completed takeovers of private targets in our sample is USD 58 million (USD 16 million), corresponding to 19% (14%) of the mean (median) deal value. Aggregating across all completed deals implies a total misallocation of capital of USD 723 billion, i.e., more than USD 18 billion per year.

4.5 Private vs. Public Targets

So far, we have focused on bids for private targets. We now consider both private and public targets and examine whether and how the relation between a bidder's cumulative abnormal return around the bid announcement and the target's asset beta varies between the two types of targets.

An important difference between public and private targets is that an observable market valuation is available for the former but not the latter. This matters because a bidder is unlikely to make a (successful) takeover bid for a public target at a price that is lower than the target's current market value. In the terminology of our model: A bidder is unlikely to successfully acquire a public target at price E_t if its market price is $\widetilde{E}_t > E_t$ because the target's shareholders are unlikely to accept such offer. Moreover, even if $\widetilde{E}_t < E_t$, we expect the relation between a bidder's CAR and public target's asset beta to be weaker than for a private target because the bidder is likely to revise its valuation in the direction of the (publicly observable) market capitalization of the target.

As a consequence, for public targets, we expect a positive (albeit weaker) relation between the bidder's CAR and target's asset beta if the beta is low and no relation if it is high. The reason is that for a public target with a low asset beta, the bidder is likely to use a discount rate that is lower than the discount rate used by the market (i.e., $r_A < \widetilde{r}_A$), so that the bidder's valuation is likely to exceed the market valuation (i.e., $E_t > \widetilde{E}_t$). For a public target with a high asset beta, instead, the market valuation is likely to exceed the bidder's valuation (i.e., $\widetilde{E}_t > E_t$). In that case, we expect the bidder to make a bid at (or above) the current market price or to not bid at all.

The situation is different for a private target: $\widetilde{E}_t$ is neither observable to the bidder nor to the target's shareholders. Hence, we expect a positive relation between a bidder's CAR and target's asset beta both for low and for high beta private targets (as predicted by our model).

[Table 5 around here.]

Table 5 presents regression results for two sub-samples: bids for private targets in columns (1) to (3) and bids for public targets in columns (4) to (6). To conserve space, we do not report the coefficient estimates and corresponding t-statistics for the control variables. Columns (1) and (4) correspond to equation (9) and the results reported in column (5) of Table 2. We find a statistically significant relation between the bidder's CAR and target's asset beta for the sample of private targets in column (1) but not for the sample of public targets in column (4).

Columns (2) and (5) show the coefficient estimates for variables indicating whether a target's asset beta falls within the bottom or top quartile of the distribution of asset betas in the sample, $\mathbb{1}\{$*Target Asset Beta in Bottom Quartile*$\}$ and $\mathbb{1}\{$*Target Asset Beta in Top Quartile*$\}$, respectively. The results indicate that bids for targets with asset betas in the bottom quartile of the beta distribution are associated with lower bidder CARs (relative to bids for targets with asset betas in the middle of the distribution) in both samples. Bids for targets with asset betas in the top quartile of the distribution, however, are associated with higher bidder CARs only in the sample of private but not in the sample of public targets. The null-hypothesis that the coefficients on $\mathbb{1}\{\textit{Target Asset Beta in Top Quartile}\}$ in columns (2) and (5) are the same is rejected by a Wald test at the 10% level and at the 5% level by a Fisher non-parametric permutation test based on 5,000 simulations (see, e.g., Cleary, 1999).

These findings are mirrored by the results shown in columns (3) and (6). In these specifications, we estimate piecewise linear regressions that allow the marginal effect of *Target Asset Beta* to differ between low beta ($\beta_A < 0.7$) and high beta ($\beta_A > 0.7$) targets. For private targets, in column (3), we find positive and statistically significant coefficients for both low and high asset betas. For public targets, in column (6), the coefficient is positive and statistically significant only for low but not for high asset betas. The null-hypothesis that the coefficients on $\max\{\textit{Target Asset Beta} - 0.7, 0\}$ in columns (3) and (6) are the same is rejected by a Wald test at the 5% level and at the 1% level by a Fisher non-parametric permutation test based on 5,000 simulations.

[Figure 2 around here.]

Figure 2 provides a graphical representation of these findings.[29] For the sample of private targets on the left, we find a positive relation between *Target Asset Beta* and *Bidder CAR* over the entire range of asset betas. In contrast, for public targets on the right, we find a significant relation only for low beta targets. For high beta public targets, the relation between *Target Asset Beta* and *Bidder CAR* is much flatter and not statistically significant.

4.6 Method of Payment

We now examine the relation between a bidder's asset beta and the method of payment proposed for takeover bids. Bidders who believe their own stock to be overvalued by the market are more likely to propose paying in stock than in cash (Shleifer and Vishny, 2003). Hence, if bidders rely

[29] The corresponding coefficient estimates are reported in Table A.4 in the appendix.

on the CAPM when assessing the value of their own equity, high beta bidders will be more likely than low beta bidders to propose stock as the method of payment.[30] To test this prediction, we estimate the following OLS regression:

$$\begin{aligned} \textit{100\% Stock} \;=\; & \alpha + \beta \times \textit{Bidder Asset Beta} + \gamma \times \textit{Target Asset Beta} \\ & + \delta' \textit{Deal Controls} + \eta' \textit{Target Controls} + \kappa' \textit{Bidder Controls} \\ & + \textit{Target Industry} \times \textit{Year Fixed Effects} + \varepsilon. \end{aligned} \tag{17}$$

100% Stock is an indicator equal to one if the bidder proposes to pay entirely with stock.[31] *Bidder (Target) Asset Beta* are the bidder's and target's asset beta, respectively. All other variables are defined as in equation (9). The standard errors are clustered by bidder industry.

[Table 6 around here.]

Table 6 presents the results. To conserve space, we do not report the coefficient estimates and corresponding t-statistics for the bidder and target controls. We find positive coefficient estimates on *Bidder Asset Beta* that are highly statistically significant in all five columns. This finding supports the prediction that high beta bidders are more likely to offer stock based payment.

4.7 Share Repurchases and Seasoned Equity Offerings

Our results on the method of payment extend beyond takeover bids. We have shown that high beta bidders are more likely to use equity to pay for the target, but if our framework is correct, then the propensity to issue equity should be higher for high beta firms whether they make acquisitions or

[30] An implicit assumption is that bidders do not perceive cash as being equally misvalued as equity.

[31] Table A.5 in the appendix shows that our findings are robust to the use of alternative variables aimed at capturing bidders' propensity to pay with stock rather than cash. Table A.6 shows that using the bidder's and target's equity betas rather than their asset betas does not change the results.

not. To a CAPM-using manager of a high beta firm, raising funds by issuing equity at the market price looks like a positive-NPV transaction – irrespective of the planned use of these funds (M&A, capital expenditures, other investments, capital structure changes, or even payouts). Repurchasing shares at the market price, on the other hand, looks like a negative-NPV investment.

Thus, we now move away from the setting of takeover bids and examine the relation between firms' asset betas and their propensity to repurchase shares or conduct seasoned equity offerings. The intuition is as follows. Firms that believe to be overvalued by the market are more likely to issue equity and less likely to repurchase shares (Baker and Wurgler, 2013). Indeed, two-thirds of CFOs state that "the amount by which our stock is undervalued or overvalued by the market" is an important or very important determinant of the decision to issue equity (Graham and Harvey, 2001, p. 2016). More than 85% of financial executives state that the "market price of our stock (if our stock is a good investment, relative to its true value)" is an important or very important determinant of the decision to repurchase shares (Brav, Graham, Harvey, and Michaely, 2005, p. 496). Hence, we predict a negative relation between a firm's asset beta and *Repurchase* – an indicator equal to one if a firm repurchases shares – and a positive relation between a firm's asset beta and *SEO* – an indicator equal to one if a firm conducts a seasoned equity offering.

To test this prediction, we estimate the following OLS regression for all public firms in Compustat between 1977 and 2015:[32]

$$\begin{aligned} \mathit{Repurchase}_t\ (\mathit{SEO}_t) \quad &= \quad \alpha + \beta \times \mathit{Asset\ Beta}_{t-1} + \gamma' \mathit{Firm\ Characteristics}_{t-1} \\ &\quad + \ \mathit{Industry} \times \ \mathit{Year\ Fixed\ Effects} + \varepsilon. \end{aligned} \tag{18}$$

Firm Characteristics is a vector of control variables commonly used in the literature on firms' share repurchase or equity issuance decisions (e.g., Dittmar, 2000; Alti and Sulaeman, 2012; Baker

[32]Descriptive statistics for this sample are presented in Table A.7 in the appendix.

and Xuan, 2016): the natural logarithm of total assets, the firm's market-to-book ratio, and the ratios of cash holdings, debt, and cash flows to assets. The standard errors are clustered by industry.

[Table 7 around here.]

Table 7 presents the results. As predicted, we find a negative and highly significant relation between *Asset Beta* and *Repurchase* and a positive and highly significant relation between *Asset Beta* and *SEO*.[33]

5 Alternative Explanations

5.1 Do Managers Use the CAPM?

Our prediction of a positive relation between the cumulative abnormal return of a bidder's stock around a bid announcement and the target's asset beta is based on the premise that managers rely on the CAPM when estimating the discount rate used to value the target. Surveys among corporate executives and valuation professionals support this assumption: The vast majority of respondents state that they always or almost always use the CAPM when estimating the cost of equity capital (Graham and Harvey, 2001; Jacobs and Shivdasani, 2012; Mukhlynina and Nyborg, 2016).

To provide further support, we test the basic implication that the discount rate used in the valuation is positively related to the target's asset beta.[34] For this purpose, we obtain data on the discount rate (*WACC*) used by investment bankers when providing fairness opinions. SDC Platinum provides this information for 1,174 bids in our sample. We then estimate by OLS:

$$\begin{aligned} WACC \;=\; & \alpha + \beta \times \textit{Target Asset Beta} + \gamma \times \textit{Beta Spread} \\ & + \; \delta \times \textit{Deal Value (Log)} + \eta \times \textit{Public Target} + \textit{Year Fixed Effects} + \varepsilon. \end{aligned} \quad (19)$$

[33]Table A.8 in the appendix shows that the results are similar when we use firms' equity rather than asset beta.

[34]Specifically, our framework implies $\partial r_A / \partial \beta_A = \mu > 0$.

Target Asset Beta is the target's asset beta, and *Beta Spread* is the difference between the target's and bidder's asset beta, as before. *Deal Value (Log)* is the natural logarithm of the value of the takeover bid in USD million. *Public Target* is an indicator for targets that are listed. We include these variables as bankers may adjust the WACC upwards for small and private targets due to their lower liquidity. The standard errors are clustered by target industry.

[Table 8 around here.]

Panel A of Table 8 presents the results. In column (1), we only control for year fixed effects. In column (2), we add *Deal Value (Log)* and *Public Target*, and in column (3), we add *Beta Spread*. The coefficient estimate on *Target Beta* is positive and statistically significant at the 1% level in all three columns. This finding supports the premise that managers rely on the CAPM when estimating the discount rate used to value the target. Note that the magnitude of the coefficient estimate – ranging from 3% in column (1) to 4% in column (3) – is likely to be a lower bound for the market risk premium used in the fairness opinions. One reason is that *Target Asset Beta* is an estimate of the beta that was actually used to compute the WACC and thus differs from the actual beta due to measurement error. This causes an attenuation bias. Another reason is that, for public targets, investment bankers may upward-adjust (downward-adjust) the market risk premium they use to compute the WACC if the DCF-implied value of the target exceeds (falls short of) its current market capitalization by a sufficiently large amount. Adjusting the market risk premium – and thus the WACC – in this manner in order to bring the fairness opinion closer to the current market price naturally reduces the coefficient estimate on *Target Asset Beta* in our regressions.

We next test another basic implication of using the CAPM: The bidder's assessment of the target's value is decreasing in its asset beta.[35] Specifically, we estimate the following OLS regression:

$$\begin{aligned} \textit{Bid-Implied Valuation} \;=\; & \alpha + \beta \times \textit{Target Asset Beta} + \gamma \times \textit{Beta Spread} \\ & + \delta' \textit{Deal Controls} + \eta' \textit{Target Controls} + \kappa' \textit{Bidder Controls} \\ & + \textit{Bidder Industry} \times \textit{Year Fixed Effects} + \varepsilon. \end{aligned} \tag{20}$$

Bid-Implied Valuation is the value of the target as implied by the takeover bid. All other variables are defined as before. The standard errors are clustered by target industry.

Panel B of Table 8 presents the results. In column (1), we use the natural logarithm of the value of the bid (in USD million) as the dependent variable.[36] In column (2), the outcome variable is the bid-implied firm value (FV) of the target scaled by its sales. In column (3), we scale the bid-implied firm value by the target's EBIT.[37] To conserve space, we do not report the coefficient estimates and associated t-statistics for the control variables.

In all three columns, we find negative and statistically significant coefficient estimates on *Target Asset Beta*. This is important for three reasons. First, it corroborates the premise that managers rely on the CAPM to compute the discount rate. Second, it supports the basic prediction that, all else equal, the bidder's assessment of the target's value is decreasing in the target's asset beta. Third, it suggests that acquisitions of targets with high asset betas do not generate larger synergies than acquisitions of low beta targets. Otherwise, one would expect the bid-implied valuations to be increasing in the targets' asset betas. This last point is important as it implies that the positive relation between a bidder's CAR and target's asset beta that we predict (and find) is unlikely to be driven by a positive correlation between the target's beta and the potential for synergies.

[35] Specifically, our framework implies $\partial E_t / \partial \beta_A = -\left(\mu \times FCF_{t+1}\right) / \left[r_f + \beta_A \times \mu - g\right]^2 < 0$.

[36] As a consequence, we do not include *Deal Value (Log)* as a control variable in column (1).

[37] Information on sales and EBIT is missing for non-U.S. targets in our sample. For this reason, the indicator for cross-boarder bids (*Crossborder*) is not included in columns (2) to (3).

5.2 Do CAPM-Betas Correlate with Future Cash Flows?

A potential concern regarding the interpretation of our findings is that asset betas may be correlated with firms' expected free cash flows and/or the synergies that can be generated by a takeover. In that case, bids for high beta targets may entail higher bidder CARs because acquisitions of high beta firms create more value. We thus examine the relation between firms' asset betas and future (realized) free cash flows as well as the relation between a target's asset beta and the combined cumulative abnormal return of the bidder and target.

We begin by examining the relation between asset betas and future (realized) free cash flows by estimating the following OLS regression for all public firms in Compustat between 1977 and 2015:

$$\frac{FCF}{Assets} = \alpha + \beta \times \textit{Asset Beta} + \gamma' \textit{Firm Characteristics} + \textit{Year Fixed Effects} + \varepsilon. \quad (21)$$

FCF/Assets is free cash flows scaled by total assets.[38] *Firm Characteristics* comprises the following variables: *Market Capitalization (Log)*, *Market-to-Book*, *Cash to Assets*, *Debt to Assets*, *ROA*, and *Cash Flow to Assets*. All variables are defined as before. The standard errors are clustered by industry.

[Table 9 around here.]

Table 9 presents the results. We do not find any evidence of a relation between asset betas and future free cash flows. This result suggests that the relation between bidder CARs and target asset betas that we find is unlikely to be driven by a correlation between asset betas and free cash flows.

[38]Specifically, we compute *FCF/Assets* as $[\text{EBIT} \times (1-\tau) + \text{D\&A} - \text{CAPEX} - \Delta\text{NWC}]\,/\text{ASSETS}$, where τ denotes the tax rate, D&A depreciation and amortization, CAPEX capital expenditures, ΔNWC the increase in net working capital, and ASSETS the book value of total assets.

5.3 Do CAPM-Betas Correlate with Synergies?

Next, we assess the relation between synergies and asset betas by regressing the combined cumulative abnormal return of a bidder and target (*Combined CAR*) on the target's asset beta.[39] Specifically, we estimate the following OLS regression:

$$\begin{aligned} \textit{Combined CAR} &= \alpha + \beta \times \textit{Target Asset Beta} + \gamma \times \textit{Beta Spread} \\ &\quad + \delta' \textit{Deal Controls} + \eta' \textit{Target Controls} + \kappa' \textit{Bidder Controls} \\ &\quad + \textit{Bidder Industry} \times \textit{Year Fixed Effects} + \varepsilon. \end{aligned} \tag{22}$$

All variables are defined as before. The standard errors are clustered by target industry.

[Table 10 around here.]

Table 10 presents the results. To conserve space, we do not report the coefficient estimates and corresponding t-statistics for the control variables. We do not find any evidence of a relation between *Target Asset Beta* and *Combined CAR*, suggesting that the relation between bidder CARs and target asset betas that we document is not driven by unobserved differences in synergies between low and high beta targets.

6 Are CAPM-Using Managers Rational?

6.1 Why Do Managers Use the CAPM?

A question raised by our findings is *why* managers rely on the CAPM despite the divergence between CAPM-implied and realized returns? This (ultimately empirical) question is not the focus of our paper. Instead, our aim is to explore the *consequences of using the CAPM.* Distinguishing between the different possible *reasons for using the CAPM* is an interesting avenue for future

[39] A caveat is that we can compute the combined CAR of bidders and targets only if the target is public.

research and may be achieved, for example, using surveys in the spirit of Graham and Harvey (2001), Brav, Graham, Harvey, and Michaely (2005), or Mukhlynina and Nyborg (2016). However, in what follows, we delineate a number of possible explanations for the widespread use of the CAPM in practice. Following Baker and Wurgler (2013), we can distinguish between rational managers/irrational markets and irrational managers/rational markets.

One possibility is that managers are fully rational: Returns deviate from the CAPM in the short-run but the CAPM ultimately holds in the long-run. Hence, it can be optimal for rational managers to use the CAPM if their goal is to maximize long-term value and if they are not financially constrained (Stein, 1996). Further, because stocks are backed not only by the firms' investment projects but also by the real options to start, modify, or abandon these projects, it is possible that the expected returns on stocks do not satisfy the CAPM even though the expected returns of the individual investment projects do (Berk, Green, and Naik, 1999; Da, Guo, and Jagannathan, 2012).

Another possibility is that managers are irrational, and the CAPM is not a good model of expected returns: Investors are rational and managers irrationally rely on the CAPM. In the simplest case, they may not be aware of the empirical shortcomings of the CAPM and the relation between bidder CARs and target asset betas. Further, learning about this relation may be hampered by the fact that most managers experience only a limited number of takeover bids and thus only receive infrequent, noisy feedback on their M&A decisions. Investment bankers who advise the firms experience a larger number of deals but are typically organized in sector teams and specialize on particular industries. As a result, they may not experience sufficient variation in target betas to learn about their relation with bidder CARs.

Finally, it is possible that managers and/or bankers are aware of the fact that realized returns differ from CAPM-implied returns but prefer the CAPM to alternative models that are more complicated to implement or explain to clients and superiors. They may also underestimate the importance of accurately estimating the cost of capital. Mukhlynina and Nyborg (2016, p. 1), for example, quote one of the respondents to their survey among valuation professionals as saying: "There seem to be lots of academics asking how analysts in the real world use CAPM or calculate the cost of capital. The answer is, people don't waste time on this. No one ever lost/made money because they calculated the WACC better than consensus."

6.2 A Suggestive Test

It is difficult to test the different alternatives above against one another, but we offer here evidence suggesting that CAPM-using managers may not be rational. We do so by regressing long-run abnormal returns of the bidders on the asset betas of the targets. The hypothesis is that, if the CAPM is a good representation of expected long-run returns, then bids for low beta targets should entail negative bidder CARs (as previously shown) that subsequently mean-revert (over longer horizons) as the market eventually learns that managers where right to use the CAPM.

We thus compute the buy-and-hold abnormal return for each bidder (*Bidder BHAR*) over different horizons and estimate the following OLS regression:

$$\begin{aligned} \textit{Bidder BHAR} &= \alpha + \beta \times \textit{Target Asset Beta} + \gamma \times \textit{Beta Spread} \\ &+ \delta' \textit{Deal Controls} + \eta' \textit{Target Controls} + \kappa' \textit{Bidder Controls} \\ &+ \textit{Bidder Industry} \times \textit{Year Fixed Effects} + \varepsilon. \end{aligned} \tag{23}$$

All variables are defined as before. The standard errors are clustered by target industry.

[Table 11 around here.]

Table 11 presents the results. To conserve space, we do not report the coefficient estimates and corresponding t-statistics for the control variables. Column (1) mirrors the findings of Table 2. The buy-and-hold abnormal return of the bidder's stock in the seven-day window around the bid announcement is increasing in the target's asset beta. Columns (2) to (5) show that we do not find any evidence of subsequent reversal in the returns. The abnormal buy-and-hold returns are not statistically different from zero starting from four trading days and up to 400 trading days after the bid announcement. The positive and statistically significant coefficient estimates in columns (6) to (9) corroborate this finding: Bidders' buy-and-hold abnormal returns from three trading days prior to the bid announcement up to 400 trading days after the announcement are positively related to the targets' asset beta. This finding suggests that bidders' reliance on the CAPM for valuation purposes has long-lasting effects on investors' wealth. Table 11 thus presents tentative evidence that it may be irrational for managers to rely on the CAPM even though it is not an accurate model of expected returns, but this last test lacks power.

7 Conclusion

The CAPM is the predominant model of risk and return taught by academics and used by practitioners to estimate the cost of capital. However, the CAPM does not fit the data: The empirical SML is flatter than the CAPM implies. We predict and find that the widespread use of the CAPM for capital budgeting and valuation purposes despite the divergence between CAPM-implied and realized returns has important implications for the market's reaction to firms' investment decisions.

In the context of mergers and acquisitions, we show that acquirers experience significantly lower cumulative abnormal returns when announcing bids for low beta targets than for high beta targets. We estimate the average loss per deal incurred by acquirers due to their reliance on the CAPM to be USD 37 million, corresponding to 12% of the average deal value and implying aggregate losses to bidders in excess of USD 10 billion per year. Relying on the CAPM also has implications for firms' financing and capital structure decisions: Low (high) beta firms are less (more) likely to offer stock rather than cash when making takeover bids, less (more) likely to issue equity, and more (less) likely to repurchase shares.

The normative implications of our study ultimately depend on how the debate about the veracity of the CAPM is settled. One view is that the CAPM holds in the long-run, but its long-run validity is hard to test (Stein, 1996). According to this view, managers are right to use the CAPM, and our findings reflect that the market is temporarily mistaken about value creation. In favor of this interpretation is Cohen, Polk, and Vuolteenaho (2009), who find that betas based on accounting cash flows forecast long-term returns (unlike simple OLS betas based on monthly stock returns).

An alternative view is that the CAPM fails to explain expected returns, even in the long-run. This view is vindicated by the fact that the asset pricing literature has failed to find any conclusive evidence in favor of the CAPM, even its conditional form. In this case, the normative implication of our paper is that managers should adopt a flatter SML than the CAPM suggests. For instance, they could shrink the beta estimates more aggressively, as suggested by Levi and Welch (2016). Yet another alternative could be to estimate discount rates based on characteristics that have been shown to predict realized returns (e.g., Daniel and Titman, 1997).

One implication of our findings, however, is clear: The simple textbook version of the CAPM in combination with OLS betas estimated based on monthly excess returns should not be used to compute firms' cost of capital.

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Figure 1: Model Calibration

This figure shows the model-implied cumulative abnormal return of a bidder's stock in response to a bid announcement as a function of the target's asset beta for different degrees of steepness of the empirical SML. The bidder's cumulative abnormal return is computed as $CAR_t^{Bidder} = \rho \times \frac{\pi \times FCF_{t+1}}{E_t^{Bidder}} \times \left[\frac{1}{r_f + (\gamma \times \beta_A + 1 - \gamma) \times \mu - g} - \frac{1}{r_f + \beta_A \times \mu - g}\right]$. The different model parameters are calibrated to match the average values in our sample of bids made by public bidders for private targets between 1977 and 2015. Specifically, we use $\rho = 92\%$, $\frac{\pi \times FCF_{t+1}}{E_t^{Bidder}} = 0.153\%$, $r_f = 5\%$, $\mu = 6\%$, and $g = 5.4\%$. We consider three different degrees of steepness of the empirical SML: $\gamma = 0$ (blue dashed line), $\gamma = 0.5$ (blue solid line), and $\gamma = 1$ (gray dashed line). The figure also shows the OLS coefficient estimates of indicator variables for different ranges of β_A (relative to the base case of $\beta_A = 0.9$, the average asset beta of the private targets in the sample) as reported in Table A.3 in the appendix (red solid line).

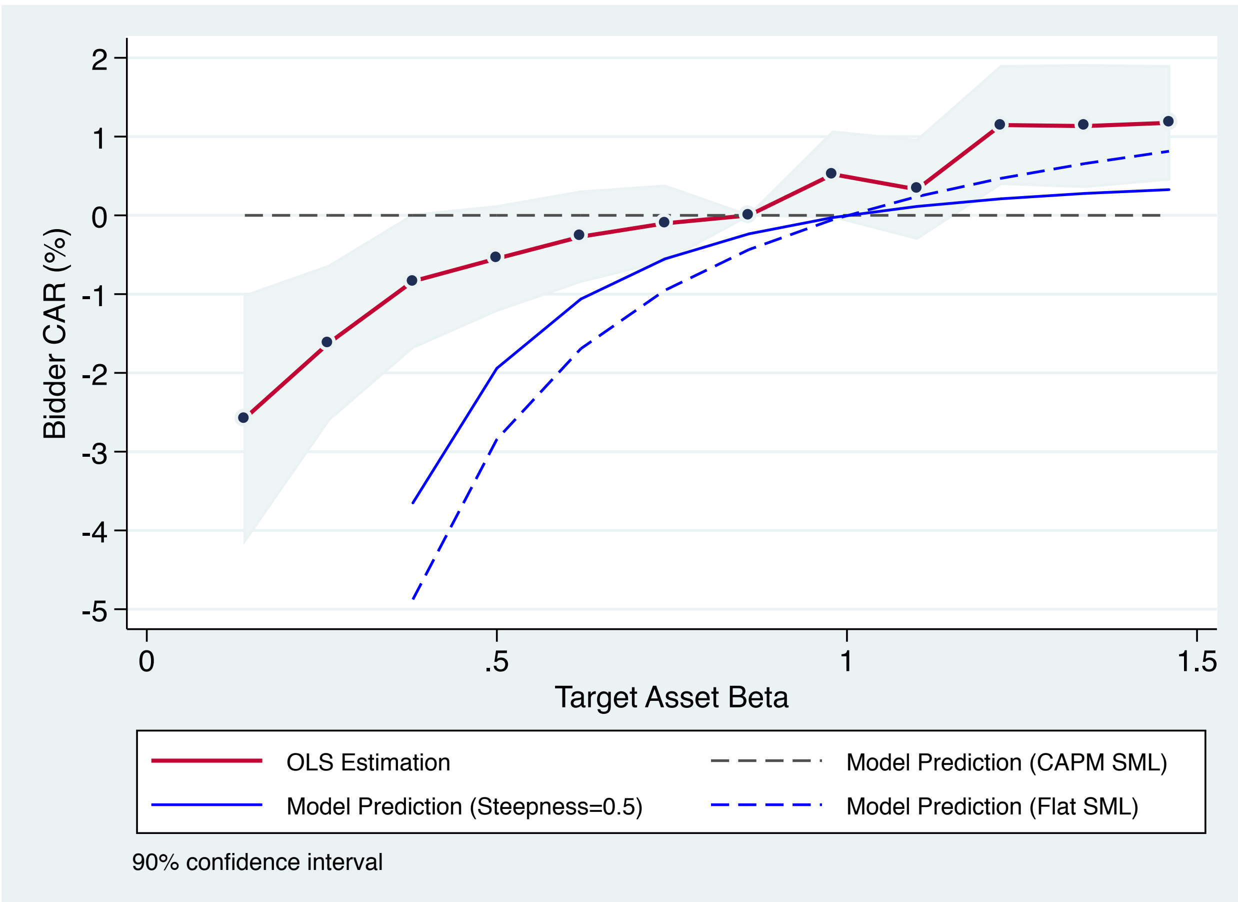

Figure 2: Private vs. Public Targets

This figure shows the OLS coefficient estimates of indicator variables for different ranges of β_A (relative to the base case of $\beta_A = 0.9$, the average asset beta of the private targets in the sample) for the sample of private targets (left panel) and the sample of public targets (right panel) as reported in Table A.4 in the appendix. The sample period is 1977 to 2015.

Table 1: Descriptive Statistics

This table presents descriptive statistics for our sample of bids for private (Panel A) and public (Panel B) targets between 1977 and 2015. *Bidder CAR* is the bidder's cumulative abnormal return around the bid announcement. *Target (Bidder) Asset Beta* is the target's (bidder's) asset beta. *Beta Spread* is the difference between the target's and bidder's asset beta. *Deal Value* is the value of the bid (in \$M). *100% Stock* is an indicator for all-stock offers. *WACC* is the discount rate used in M&A fairness opinions. All continuous variables are winsorized at the 1st and 99th percentile. Detailed definitions are provided in the appendix.

Panel A – Private Targets	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	Bids for Private Targets with a CPI-Adjusted Deal Value ≥ \$50M, 1977-2015							
Variable:	Observations	Mean	SD	Min.	*p*25	*p*50	*p*75	Max.
Bidder CAR	14,744	2.0%	8.2%	-20.5%	-2.3%	1.1%	5.6%	27.9%
Target Asset Beta	17,885	0.86	0.33	0.17	0.62	0.86	1.11	1.55
Bidder Asset Beta	18,163	0.87	0.32	0.20	0.64	0.84	1.11	1.54
Beta Spread	17,707	-0.01	0.25	-0.74	-0.06	0.00	0.03	0.76
Deal Value (Log)	18,485	4.91	1.07	3.29	4.09	4.70	5.52	9.08
Deal Value (in \$M)	18,485	297	699	27	60	110	250	8,799
Deal Value (in \$M, CPI-Adjusted)	18,485	388	882	51	82	148	334	11,437
100% Stock	18,482	0.13	0.33	0	0	0	0	1
WACC	117	14.1%	4.9%	7.0%	11.0%	13.0%	15.0%	30.0%

Panel B – Public Targets	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	Bids for Public Targets with a CPI-Adjusted Deal Value ≥ \$50M, 1977-2015							
Variable:	Observations	Mean	SD	Min.	*p*25	*p*50	*p*75	Max.
Bidder CAR	7,296	-0.6%	7.7%	-20.5%	-4.6%	-0.7%	3.1%	27.9%
Target Asset Beta	7,879	0.82	0.36	0.17	0.53	0.82	1.11	1.55
Bidder Asset Beta	7,932	0.81	0.34	0.20	0.55	0.80	1.09	1.54
Beta Spread	7,794	0.01	0.21	-0.74	0.00	0.00	0.00	0.76
Deal Value (Log)	8,095	5.59	1.49	3.29	4.38	5.33	6.55	9.08
Deal Value (in \$M)	8,095	921	1,852	27	80	206	699	8,799
Deal Value (in \$M, CPI-Adjusted)	8,095	1,258	2,430	51	121	307	1,019	11,437
100% Stock	8,091	0.33	0.47	0	0	0	1	1
WACC	1,064	13.1%	3.9%	7.0%	10.5%	12.3%	14.5%	30.0%

Table 2: Cumulative Abnormal Return (CAR) of Bidders' Stock around Bid Announcements

This table presents OLS estimates of the sensitivity of the cumulative abnormal return of the bidder's stock during the seven-day window around the bid announcement (*Bidder CAR*) to the target's asset beta. The sample period is 1977 to 2015. Only bids for private targets are included. *Target (Bidder) Controls* is a vector of target (bidder) characteristics: *Market-to-Book*, *ROA*, *Cash Flow to Assets*, *Debt to Assets*, and *Cash to Assets*. For private targets, these variables are average values of the corresponding variables across all public firms in Compustat with the same three-digit primary SIC code. All other variables are defined as in Table 1. Detailed definitions of all variables are provided in the appendix. t-statistics based on standard errors clustered by the target's (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)
Sample:	Private Targets				
Dependent Variable:	Bidder CAR (in Percentage Points)				
Target Asset Beta	1.02***	1.34***	1.73***	1.49***	2.55***
	(3.02)	(4.20)	(4.72)	(4.14)	(5.06)
Beta Spread					-1.36***
					(-2.60)
Deal Value (Log)		0.66***	0.65***	0.59***	0.59***
		(7.37)	(7.34)	(6.82)	(6.69)
Equity		0.59**	0.60**	0.57*	0.51*
		(2.24)	(2.26)	(1.87)	(1.69)
Cash		0.30	0.28	0.48	0.44
		(1.07)	(0.98)	(1.45)	(1.34)
Toehold		-0.08	-0.15	-0.11	-0.10
		(-0.20)	(-0.36)	(-0.26)	(-0.24)
Hostile		-2.26**	-2.44**	-2.82**	-3.22***
		(-2.19)	(-2.26)	(-2.26)	(-2.76)
Same Industry		0.11	0.12	0.12	0.14
		(0.65)	(0.71)	(0.82)	(0.96)
Crossborder		-0.14	-0.14	-0.06	-0.09
		(-0.63)	(-0.61)	(-0.26)	(-0.37)
Poison		-0.60	-0.66	-0.51	-0.47
		(-0.87)	(-0.90)	(-0.49)	(-0.45)
Tender		-0.30	-0.36	-0.57	-0.72
		(-0.29)	(-0.34)	(-0.49)	(-0.63)
Multiple Bidders		-0.40	-0.38	0.07	0.03
		(-0.54)	(-0.51)	(0.09)	(0.04)
Relative Size		-0.06***	-0.06***	-0.06***	-0.06***
		(-7.25)	(-7.20)	(-7.51)	(-7.59)
Bidder Size (Log)		-0.94***	-0.94***	-0.96***	-0.96***
		(-12.40)	(-12.33)	(-12.50)	(-12.56)
Bidder SDC Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Target Controls	No	No	Yes	Yes	Yes
Bidder Controls	No	No	No	Yes	Yes
Observations	13,916	13,599	13,486	12,209	12,109

Table 3: Two-Stage-Least-Squares (2SLS) Instrumental Variable Estimation

This table presents 2SLS estimates of the sensitivity of *Bidder CAR* to *Target Asset Beta*. The sample period is 1980 to 2015. Only bids for private targets are included. *Deal Controls* is a vector comprising all deal-level controls included in columns (2) to (4) of Table 2: *Deal Value (Log)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same Industry*, *Crossborder*, *Poison*, *Tender*, *Multiple Bidders*, *Relative Size*, and *Bidder Size (Log)*. All other variables are defined as in Table 2. Detailed definitions are provided in the appendix. t-statistics based on standard errors clustered by the target's (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A – 1st Stage of 2SLS	(1)	(2)	(3)	(4)	(5.a)	(5.b)
Sample:			Private Targets			
Dependent Variable:	Target Asset Beta	Target Asset Beta	Target Asset Beta	Target Asset Beta	Target Asset Beta	Beta Spread
Target Noise Beta	3.43***	3.40***	2.18***	2.19***	2.24***	2.34***
	(11.08)	(11.44)	(15.8)	(15.76)	(15.16)	(13.23)
Bidder Noise Beta					-0.15	-2.46***
					(1.06)	(12.01)
Bidder SDC Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal Controls	No	Yes	Yes	Yes	Yes	Yes
Target Controls	No	No	Yes	Yes	Yes	Yes
Bidder Controls	No	No	No	Yes	Yes	Yes
Observations	13,385	13,081	12,972	11,740	11,739	11,739

Panel B – 2nd Stage of 2SLS	(1)	(2)	(3)	(4)		(5)
Sample:			Private Targets			
Dependent Variable:			Bidder CAR (in Percentage Points)			
Target Asset Beta (instrumented)	1.86**	2.09**	3.03**	2.83*		4.45*
	(2.09)	(2.41)	(1.99)	(1.72)		(1.72)
Beta Spread (instrumented)						-2.32
						(1.18)
Bidder SDC Industry × Year FE	Yes	Yes	Yes	Yes		Yes
Deal Controls	No	Yes	Yes	Yes		Yes
Target Controls	No	No	Yes	Yes		Yes
Bidder Controls	No	No	No	Yes		Yes
Observations	13,385	13,081	12,972	11,740		11,739

Table 4: Cross-Sectional Variation

This table presents OLS estimates of the sensitivity of the cumulative abnormal return of the bidder's stock during the seven-day window around the bid announcement (*Bidder CAR*) to the target's asset beta as function of cross-sectional characteristics. The sample period is 1977 to 2015. Only bids for private targets are included. *High Growth* is an indicator equal to one if the compound annual growth rate of aggregate sales in the target's (SIC3-)industry during the three years preceding the takeover bid is larger than the sample median. *High Relative Size* is an indicator equal to one if *Relative Size* is larger than the sample median. *CAPM Usage* is an indicator equal to one if the bidder's 10K, 10Q, or 8K filings of the three years prior to the bid announcement contain the words "CAPM" or "Capital Asset Pricing Model." *Deal Controls* is a vector comprising all deal-level controls included in column (5) of Table 2: *Beta Spread*, *Deal Value (Log)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same Industry*, *Crossborder*, *Poison*, *Tender*, *Multiple Bidders*, *Relative Size*, and *Bidder Size (Log)*. All other variables are defined as in Table 2. Detailed definitions are provided in the appendix. *(Interacted)* indicates that all control variables and fixed effects are interacted with the cross-sectional characteristic of interest, allowing their coefficients to depend on the value of *High Growth*, *High Relative Size*, and *CAPM Usage*, respectively. *t*-statistics based on standard errors clustered by the target's (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)
Sample:	Private Targets		
Dependent Variable:	Bidder CAR (in Percentage Points)		
Target Asset Beta × High Growth	2.71**		
	(2.08)		
Target Asset Beta × High Relative Size		2.86**	
		(2.31)	
Target Asset Beta × CAPM Usage			10.95**
			(2.03)
Target Asset Beta	1.44*	1.39**	2.37***
	(1.93)	(2.07)	(4.24)
Bidder SDC Industry × Year FE (Interacted)	Yes	Yes	Yes
Deal Controls (Interacted)	Yes	Yes	Yes
Target Controls (Interacted)	Yes	Yes	Yes
Bidder Controls (Interacted)	Yes	Yes	Yes
Observations	11,518	11,503	12,109

Table 5: Bidder CAR – Private vs. Public Targets

This table presents OLS estimates of the sensitivity of the cumulative abnormal return of the bidder's stock during the seven-day window around the bid announcement (*Bidder CAR*) to the target's asset beta. The sample period is 1977 to 2015. $\mathbb{1}\{$Target Asset Beta in Bottom (Top) Quartile$\}$ is an indicator equal to one if the target's asset beta is in the bottom (top) quartile of the distribution. $\min\{\text{Target Asset Beta}, 0.7\}$ is the minimum of *Target Asset Beta* and 0. $\max\{\text{Target Asset Beta} - 0.7, 0\}$ is the maximum of *Target Asset Beta* − 0.7 and 0. *Deal Controls* is a vector comprising all deal-level controls included in column (5) of Table 2: *Beta Spread*, *Deal Value (Log)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same Industry*, *Crossborder*, *Poison*, *Tender*, *Multiple Bidders*, *Relative Size*, and *Bidder Size (Log)*. All other variables are defined as in Table 2. Detailed definitions are provided in the appendix. t-statistics based on standard errors clustered by the target's (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Private Targets			Public Targets		
Dependent Variable:	Bidder CAR (in Percentage Points)					
Target Asset Beta	2.55***			0.40		
	(5.06)			(0.32)		
$\mathbb{1}\{$Target Asset Beta in Bottom Quartile$\}$		-0.59**			-1.20**	
		(-2.09)			(-2.36)	
$\mathbb{1}\{$Target Asset Beta in Top Quartile$\}$		0.88***			-0.04	
		(3.27)			(-0.07)	
$\min\{\text{Target Asset Beta}, 0.7\}$			3.20***			3.90**
			(3.18)			(2.06)
$\max\{\text{Target Asset Beta} - 0.7, 0\}$			2.25***			-1.20
			(3.67)			(-0.77)
Bidder SDC Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Target Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bidder Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,109	12,109	12,109	3,894	3,894	3,894

Table 6: Method of Payment

This table presents OLS estimates of the sensitivity of the propensity to offer an all-stock payment to the bidder's asset beta (*Bidder Asset Beta*). The sample period is 1977 to 2015. *100% Stock* is an indicator equal to one if the proposed payment is 100% stock. All other variables are defined as in Table 2. Detailed definitions are provided in the appendix. *t*-statistics based on standard errors clustered by the bidder's (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)
Sample:	Private and Public Targets				
Dependent Variable:	100% Stock				
Bidder Asset Beta	9.50***	13.58***	8.20***	7.95***	8.26***
	(4.01)	(6.60)	(5.23)	(4.65)	(4.61)
Target Asset Beta					-1.22
					(-0.53)
Deal Value (Log)		3.41***	3.47***	3.47***	3.49***
		(7.00)	(7.04)	(7.05)	(7.10)
Toehold		-7.11***	-6.22***	-6.38***	-6.41***
		(-2.93)	(-2.64)	(-2.67)	(-2.69)
Hostile		-7.57***	-8.48***	-8.84***	-8.75***
		(-3.99)	(-3.65)	(-3.79)	(-3.75)
Same Industry		0.39	0.09	0.04	-0.02
		(0.30)	(0.11)	(0.04)	(-0.02)
Crossborder		-5.55***	-5.45***	-5.33***	-5.15***
		(-5.47)	(-5.58)	(-5.58)	(-5.59)
Poison		15.91***	16.16***	16.18***	15.94***
		(8.71)	(8.81)	(9.10)	(9.23)
Tender		-16.92***	-16.05***	-15.75***	-15.81***
		(-10.28)	(-10.52)	(-10.55)	(-10.60)
Multiple Bidders		-0.37	-0.42	-0.43	-0.39
		(-0.28)	(-0.27)	(-0.28)	(-0.25)
Relative Size		-0.14***	-0.11***	-0.12***	-0.12***
		(-3.57)	(-3.00)	(-3.13)	(-3.17)
Bidder Size (Log)		-1.52***	-1.26***	-1.27***	-1.28***
		(-4.97)	(-4.44)	(-4.40)	(-4.41)
Target SDC Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Bidder Controls	No	No	Yes	Yes	Yes
Target Controls	No	No	No	Yes	Yes
Observations	25,772	21,063	18,762	18,423	18,348

Table 7: Share Repurchases and Seasoned Equity Offerings

This table presents OLS estimates of the sensitivity of the propensity to repurchase shares (*Repurchase*) and to conduct seasoned equity offerings (*SEO*) to the firm's asset beta (*Asset Beta*). The sample period is 1977 to 2015. All public firms in Compustat are included. Detailed definitions of all variables are provided in the appendix. t-statistics based on standard errors clustered by the firm's (SIC2-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Sample:	Public Firms in Compustat			
Dependent Variable:	Repurchase_t		SEO_t	
Asset Beta_{t-1}	-10.95***	-11.01***	18.33***	17.07***
	(-5.45)	(-6.49)	(10.68)	(10.56)
Market $\text{Capitalization}_{t-1}$ (Log)		4.86***		4.91***
		(21.74)		(18.33)
$\text{Market-to-Book}_{t-1}$		-0.42***		0.38***
		(-6.79)		(3.81)
Cash to Assets_{t-1}		-2.72		1.43
		(-0.79)		(0.53)
Debt to Assets_{t-1}		-10.77***		-3.37
		(-5.30)		(-1.09)
ROA_{t-1}		2.60		9.25**
		(0.77)		(2.46)
Cash Flow to Assets_{t-1}		4.12		-13.70***
		(1.19)		(-3.24)
SIC2 Industry × Year FE	Yes	Yes	Yes	Yes
Observations	319,143	219,486	318,771	219,162

Table 8: Discount Rate Used in M&A Fairness Opinions and Bid-Implied Target Valuations

This table presents OLS estimates of the sensitivity of the discount rate (*WACC*) used in fairness opinions on proposed M&A transactions (Panel A) and bid-implied target valuations (Panel B) to the target's asset beta. The sample period is 1977 to 2015. *Public Target* is an indicator for public targets. *FV/Sales* and *FV/EBIT* are the ratios of the target's bid-implied firm value to its sales and EBIT, respectively. *Deal Controls* is a vector comprising *Beta Spread*, *Deal Value (Log)* (omitted in column (1) of Panel B), *Equity*, *Cash*, *Toehold*, *Hostile*, *Same Industry*, *Crossborder* (omitted in columns (2) and (3) of Panel B), *Poison*, *Tender*, *Multiple Bidders*, *Relative Size*, and *Bidder Size (Log)*. All other variables are defined as in Table 2. Detailed definitions are provided in the appendix. *t*-statistics based on standard errors clustered by the target's (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A	(1)	(2)	(3)
Sample:	Private and Public Targets		
Dependent Variable:	WACC Used in DCF Analysis (in Percentage Points)		
Target Asset Beta	3.03***	3.69***	3.99***
	(5.76)	(12.92)	(11.19)
Beta Spread			-1.81**
			(-2.46)
Deal Value (Log)		-1.30***	-1.30***
		(-8.90)	(-9.17)
Public Target		-0.88***	-0.94***
		(-2.85)	(-2.99)
Year FE	Yes	Yes	Yes
Observations	1,174	1,174	1,171

Panel B	(1)	(2)	(3)
Sample:	Private and Public Targets		
Dependent Variable:	Deal Value (Log)	FV/Sales	FV/EBIT
Target Asset Beta	-0.20***	-2.58***	-8.47***
	(-2.63)	(-2.72)	(-2.66)
Bidder SDC Industry × Year FE	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes
Target Controls	Yes	Yes	Yes
Bidder Controls	Yes	Yes	Yes
Observations	18,370	4,196	3,116

Table 9: Future Realized Free Cash Flows

This table presents OLS estimates of the sensitivity of a firm's realized free cash flows in future periods scaled by total assets (*FCF/Assets*) to the firm's lagged asset beta. All reported coefficient estimates have been multiplied with 100 to improve readability. The sample period is 1977 to 2015. All public firms in Compustat are included. Detailed definitions of all variables are provided in the appendix. t-statistics based on standard errors clustered by (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Sample:	Public Firms in Compustat			
Dependent Variable:	$\frac{FCF_t}{Assets_t}$	$\frac{FCF_{t+1}}{Assets_{t+1}}$	$\frac{FCF_{t+2}}{Assets_{t+2}}$	$\frac{FCF_{t+3}}{Assets_{t+3}}$
Asset Beta$_{t-1}$	-0.32	-0.10	-0.34	-0.43
	(-0.20)	(-0.06)	(-0.22)	(-0.29)
Market Capitalization$_{t-1}$ (Log)	1.06***	1.29***	1.45***	1.47***
	(4.42)	(4.94)	(5.87)	(6.16)
Market-to-Book$_{t-1}$	-0.42***	-0.40***	-0.34***	-0.29***
	(-6.22)	(-5.58)	(-4.81)	(-3.66)
Cash to Assets$_{t-1}$	-17.14***	-16.07***	-15.04***	-14.30***
	(-6.50)	(-4.65)	(-3.88)	(-3.50)
Debt to Assets$_{t-1}$	5.18***	4.67***	3.80**	3.28**
	(3.22)	(2.78)	(2.21)	(1.98)
ROA$_{t-1}$	-4.84	4.09	2.81	7.43
	(-0.51)	(0.41)	(0.36)	(0.89)
Cash Flow to Assets$_{t-1}$	36.21***	24.57**	22.96***	15.86*
	(3.54)	(2.33)	(2.83)	(1.88)
Year FE	Yes	Yes	Yes	Yes
Observations	208,399	187,045	168,898	152,541

Table 10: Combined CAR of Bidder and Target

This table presents OLS estimates of the sensitivity of the combined cumulative abnormal returns of the bidder's and target's stock during the seven-day window around the bid announcement (*Combined CAR*) to the target's asset beta. The sample period is 1977 to 2015. Only public targets are included. *Deal Controls* is a vector comprising all deal-level controls included in column (5) of Table 2: *Beta Spread*, *Deal Value (Log)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same Industry*, *Crossborder*, *Poison*, *Tender*, *Multiple Bidders*, *Relative Size*, and *Bidder Size (Log)*. All other variables are defined as in Table 2. Detailed definitions are provided in the appendix. t-statistics based on standard errors clustered by the target's (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Sample:	Public Targets			
Dependent Variable:	Combined CAR (in Percentage Points)			
Target Asset Beta	-0.60	-0.21	-0.71	0.45
	(-1.07)	(-0.28)	(-0.82)	(0.40)
Beta Spread				-1.63
				(-1.59)
Bidder SDC Industry × Year FE	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes
Target Controls	No	Yes	Yes	Yes
Bidder Controls	No	No	Yes	Yes
Observations	5,079	4,952	4,324	4,273

Table 11: Bidder Buy-and-Hold Abnormal Return (BHAR)

This table presents OLS estimates of the sensitivity of the buy-and-hold abnormal return of the bidder's stock over different event windows (*Bidder BHAR*) to the target's asset beta. [x,y] denotes an event window from $t = x$ to $t = y$ for a bid announced on date $t = 0$. The sample period is 1977 to 2015. Only bids for private targets are included. *Deal Controls* is a vector comprising all deal-level controls included in column (5) of Table 2: *Beta Spread*, *Deal Value (Log)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same Industry*, *Crossborder*, *Poison*, *Tender*, *Multiple Bidders*, *Relative Size*, and *Bidder Size (Log)*. All other variables are defined as in Table 2. Detailed definitions are provided in the appendix. t-statistics based on standard errors clustered by the target's (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample:	Private Targets								
Dependent Variable:	Bidder BHAR (in Percentage Points)								
Event Window:	[-3,+3]	[+4,+100]	[+4,+200]	[+4,+300]	[+4,+400]	[-3,+100]	[-3,+200]	[-3,+300]	[-3,+400]
Target Asset Beta	2.75***	0.42	2.82	4.50	6.47	3.63*	6.21**	7.49*	8.95*
	(4.29)	(0.22)	(0.96)	(1.09)	(1.35)	(1.75)	(2.08)	(1.88)	(1.88)
Bidder SDC Ind. × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Target Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bidder Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,281	10,220	10,038	9,817	9,578	10,219	10,037	9,816	9,577

Appendix to
“CAPM-Based Company (Mis)valuations”

Variable	Definition
Above 50% Stock	Indicator equal to one if the proposed payment consists of more than 50% stock.
Asset Beta	Equally weighted average asset beta of all public firms in CRSP with the same three-digit primary SIC code. Asset betas are computed as $\beta_A = \beta_E / [1 + (1-\tau) \times D/E]$, where β_E is the equity beta, τ is the statutory tax rate in the highest bracket, D is total debt ($DLT + DLC$), and E is the market value of equity. Using alternative methodologies to delever the equity betas does not materially affect the results. Equity betas are estimated by regressing five years of monthly excess returns (RET minus the risk-free rate obtained from Kenneth French's webpage, *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*) on excess returns of the CRSP value-weighted portfolio (including dividends). We use CRSP sharecodes 10 and 11 and compute the value-weighted average beta in case of multiple securities per firm. We drop estimates based on less than 36 months of return data. Further, we drop observations for which the estimated beta is negative, and we drop the same number of observations in the right tail of the distribution of estimated betas.
Beta Spread	Target Asset Beta minus Bidder Asset Beta.
Beta Spread (Equity)	Target Equity Beta minus Bidder Equity Beta.
Bidder Asset Beta	Equally weighted average asset beta of all public firms in CRSP with the same three-digit primary SIC code as the bidder, estimated one month prior to the bid announcement. (See *Asset Beta* for details of the estimation of individual betas.)
Bidder BHAR	Buy-and-hold abnormal return of the bidder's stock. [x,y] denotes an event window from $t = x$ to $t = y$ for a bid announced on date $t = 0$. The buy-and-hold abnormal return for bidder i is given by $\text{BHAR}_i \equiv \text{BH}_i - \text{BH}_i^{\text{Match}}$, where BH_i is the buy-and-hold return of bidder i (during the event window from $t = x$ to $t = y$), and $\text{BH}_i^{\text{Match}}$ is the buy-and-hold return on a portfolio of firms matched to bidder i based on industry, size, and Tobin's Q (e.g., Savor and Lu, 2009). We first match bidder i to all public firms in CRSP with the same three-digit primary SIC code. Next, we compute the Mahalanobis distance to all matched firms in terms of size and Tobin's Q to identify the ten closest industry peers. $\text{BH}_i^{\text{Match}}$ is then computed as the weighted average buy-and-hold return of these ten closest industry peers, where the weights are chosen such that closer peers receive greater weight. If there are less than ten peers (because there are not enough firms in the same industry), the matched portfolio contains less than ten firms. The weight assigned to peer j of bidder i is $w_{i,j} = K(d_{i,j}/h_i) / \sum_{k=1}^{N_i} K(d_{i,k}/h_i)$, where N_i is the number of peers matched to bidder i, $d_{i,j}$ is the Mahalanobis distance between bidder i and peer j, $K(\cdot)$ is the Gaussian density function, and h_i is equal to the Mahalanobis distance to the nearest matched peer (see, e.g., Todd, 1999).
Bidder CAR	Cumulative abnormal return of the bidder's stock over the seven-day window around the bid announcement (i.e., from $t = -3$ to $t = +3$ for a bid announced on date $t = 0$). Abnormal returns are market adjusted returns of CRSP sharecodes 10 and 11, using the CRSP value-weighted portfolio as the market proxy. Outliers are dropped by trimming the final distribution of CARs at the 0.5% level in each tail.
Bidder Equity Beta	Equally weighted average equity beta of all public firms in CRSP with the same three-digit primary SIC code as the bidder, estimated one month prior to the bid announcement. (See *Asset Beta* for details of the estimation of individual betas.)
Bidder Noise Beta	Equally weighted average noise beta of all public firms in CRSP with the same three-digit primary SIC code as the bidder, estimated one month prior to the bid announcement. (See *Noise Beta* for details of the estimation of individual betas.)
Bidder Size (Log)	Natural logarithm of the market capitalization of the bidder in USD million four days prior to the bid announcement.

Variable	Definition
CAPM Usage	Indicator equal to one if the bidder's 10K, 10Q, or 8K filings of the three years prior to the bid announcement contain the words "CAPM" or "Capital Asset Pricing Model."
Cash	Indicator equal to one if the proposed payment includes cash.
Cash Flow to Assets	Net income (ib) + D&A (dp) / total assets (at).
Cash to Assets	Total cash and cash equivalents (che) / total assets (at).
Combined CAR	Weighted average of the cumulative abnormal returns of the bidder's and target's stock over the seven-day window around the bid announcement. (See *Bidder CAR* for details of the estimation of the cumulative abnormal returns.)
Crossborder	Indicator equal to one if the target's and bidder's headquarters are located in different countries.
Deal Value (Log)	Natural logarithm of the value of the takeover bid in USD million.
Deal Value (in $M)	Value of the takeover bid in USD million.
Deal Value (in $M, CPI-Adjusted)	Inflation-adjusted value of the takeover bid in USD million (in December 2015 terms).
Debt to Assets	Total debt (dlc + dltt) / total assets (at).
Equity	Indicator equal to one if the proposed payment includes stock.
FCF/Assets	$[\text{EBIT} \times (1-\tau) + \text{D\&A} - \text{CAPEX} - \Delta\text{NWC}]\,/\text{ASSETS}$, where EBIT is earnings before interest and taxes (Compustat item ebit, or oiadp if ebit is missing, or pi + xint − spi − nopi if both ebit and oiadp are missing), τ is the statutory tax rate in the highest bracket, D&A is depreciation and amortization (Compustat item dp, or xdp if dp is missing, or dpc if both dp and xdp are missing), CAPEX is capital expenditures (Compustat item capx, or capxv if capx is missing), ΔNWC is the increase in net working capital (Compustat items recch + invch + apalch + aoloch, or if missing: $-$ (rect $-$ rect$_{t-1}$) $-$ (invt $-$ invt$_{t-1}$) + (ap $-$ ap$_{t-1}$) $-$ (aco $-$ lco $-$ aco$_{t-1}$ + lco$_{t-1}$)), and ASSETS is the book value of total assets (Compustat item at).
FV	Bid-implied firm value of the target, defined as EV + ASSETS − BVE. EV is the bid-implied equity value of the target, defined as the equity value indicated in SDC, or the deal value divided by the percentage of equity acquired if the equity value is missing but the deal is completed, or the deal value divided by the percentage of equity sought if the equity value is missing and the deal is withdrawn. ASSETS is the book value of total assets (Compustat item at), and BVE is the book value of equity (Compustat item ceq).
FV/EBIT	Bid-implied firm value of the target divided by the target's EBIT.
FV/Sales	Bid-implied firm value of the target divided by the target's sales.
High Growth	Indicator equal to one if the compound annual growth rate of aggregate sales in the target's (SIC3-)industry during the three years preceding the takeover bid is larger than the sample median.
High Relative Size	Indicator equal to one if *Relative Size* is larger than the sample median.

Variable	Definition
HMFFS	Dollar amount of hypothetical mutual fund fire sales, assuming that each position in an affected fund's portfolio is liquidated in proportion to its portfolio weight, scaled by the dollar volume of trading in the stock.
Hostile	Indicator equal to one if the initial bid is hostile.
Market Capitalization (Log)	Natural logarithm of the market value of equity in USD million.
Market-to-Book	Market capitalization (prc $\times$ csho) / shareholders' equity (ceq).
$\max\{\text{Target Asset Beta} - 0.7, 0\}$	Maximum of *Target Asset Beta* $-$ 0.7 and 0.
$\min\{\text{Target Asset Beta}, 0.7\}$	Minimum of *Target Asset Beta* and 0.7.
Multiple Bidders	Indicator equal to one if there is more than one bidder.
Noise Beta	In-sample covariance between the estimated noise component in a firm's realized excess stock returns and the realized excess returns on the market proxy, scaled by the in-sample variance of the excess market returns. The noise components are estimated as the fitted values from a regression of realized excess returns on hypothetical mutual fund fire sales. Individual firms' noise betas are delevered and aggregated at the industry level in analogy to the construction of *Asset Beta*.
Poison	Indicator equal to one if the target uses a defense mechanism.
Public Target	Indicator equal to one if the target is listed.
Relative Size	Deal value divided by the market capitalization of the bidder four days prior to the bid announcement.
Repurchase	Indicator equal to one if a firm repurchases shares.
ROA	Return on assets (ib / at).
Same Industry	Indicator equal to one if the bidder and target operate in the same industry as defined by the first three digits of their primary SIC codes.
SEO	Indicator equal to one if a firm does a seasoned equity offering.
Stock vs. Cash	Indicator equal to one (zero) if 100% of the proposed payment is in stock (cash). Deals for which the proposed payment comprises both stock and cash are excluded.
Target Asset Beta	Equally weighted average asset beta of all public firms in CRSP with the same three-digit primary SIC code as the target, estimated one month prior to the bid announcement. (See *Asset Beta* for details of the estimation of individual betas.)
Target Equity Beta	Equally weighted average equity beta of all public firms in CRSP with the same three-digit primary SIC code as the target, estimated one month prior to the bid announcement. (See *Asset Beta* for details of the estimation of individual betas.)
Target Noise Beta	Equally weighted average noise beta of all public firms in CRSP with the same three-digit primary SIC code as the target, estimated one month prior to the bid announcement. (See *Noise Beta* for details of the estimation of individual betas.)

Variable	Definition
Tender	Indicator equal to one if the bid is a tender offer.
Toehold	Fraction of the target's equity held by the bidder before the bid.
WACC	Average of the high and low discount rates (SDC items FO_DCF_RATE_HI and FO_DCF_RATE_LOW) used for discounted cash flow analyses in M&A fairness opinions.
100% Stock	Indicator equal to one if 100% of the offered payment is in stock.
$\mathbb{1}\{a <$ Target Asset Beta $\leq b\}$	Indicator equal to one if the target's asset beta is larger than a but smaller than (or equal to) b.
$\mathbb{1}\{$Target Asset Beta in Bottom Quartile$\}$	Indicator equal to one if the target's asset beta is in the bottom quartile of the distribution.
$\mathbb{1}\{$Target Asset Beta in Top Quartile$\}$	Indicator equal to one if the target's asset beta is in the top quartile of the distribution.

Figure A.1: Non-Parametric Regression of *Target Asset Beta* on *Target Noise Beta*

This figure shows the coefficient estimates from an OLS regression of *Target Asset Beta* on indicator variables for different ranges of *Target Noise Beta*. The sample period is 1980 to 2015.

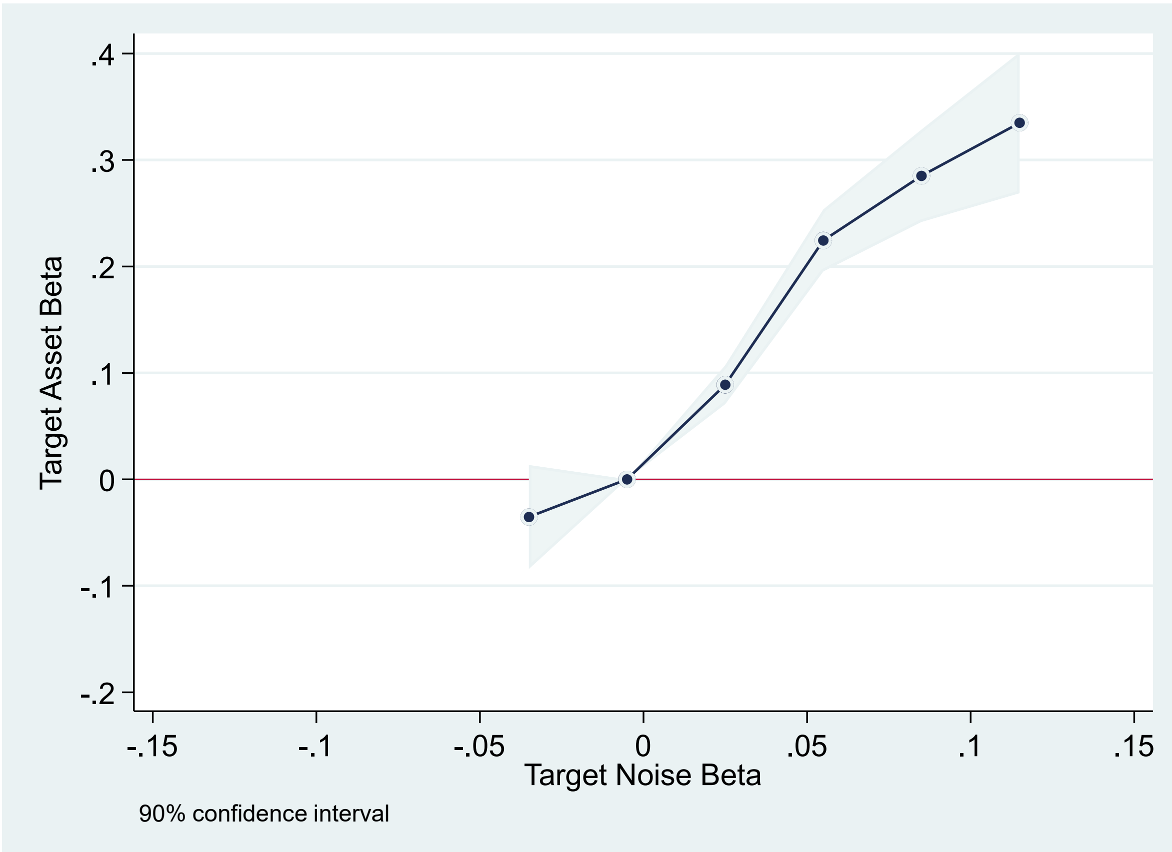

Table A.1: Alternative CAR Models

This table presents OLS estimates of the sensitivity of the cumulative abnormal return of the bidder's stock during the seven-day window around the bid announcement (*Bidder CAR*) to the target's asset beta. The sample period is 1977 to 2015. Only bids for private targets are included. In column (1), *Bidder CAR* is defined as the return of the bidder's stock minus the return of the CRSP value-weighted portfolio. In column (2), *Bidder CAR* is defined as the return of the bidder's stock minus the expected return implied by the CAPM. In columns (3) and (4), *Bidder CAR* is defined as the return of the bidder's stock minus the expected return implied by the Fama-French three factor model (Fama and French, 1993) and Carhart four factor model (Carhart, 1997), respectively. *Deal Controls* is a vector comprising all deal-level controls included in column (5) of Table 2: *Beta Spread*, *Deal Value (Log)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same Industry*, *Crossborder*, *Poison*, *Tender*, *Multiple Bidders*, *Relative Size*, and *Bidder Size (Log)*. All other variables are defined as in Table 2. Detailed definitions are provided in the appendix. t-statistics based on standard errors clustered by the target's (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Sample:	Private Targets			
Dependent Variable:	Bidder CAR (in Percentage Points)			
CAR Model:	Market Adjusted	Market Model	3 Factors	4 Factors
Target Asset Beta	2.55***	2.19***	2.13***	2.23***
	(5.06)	(4.61)	(4.43)	(4.66)
Bidder SDC Industry × Year FE	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes
Target Controls	Yes	Yes	Yes	Yes
Bidder Controls	Yes	Yes	Yes	Yes
Observations	12,109	12,061	12,061	12,060

Table A.2: Sensitivity of Bidder CAR to Target Equity Beta

This table presents OLS estimates of the sensitivity of the cumulative abnormal return of the bidder's stock during the seven-day window around the bid announcement (*Bidder CAR*) to the target's equity beta. The sample period is 1977 to 2015. Only bids for private targets are included. *Target Equity Beta* is the equity beta of the target. *Beta Spread (Equity)* is the difference between the target's and the bidder's equity beta. *Deal Controls* is a vector comprising all deal-level controls included in columns (2) to (4) of Table 2: *Deal Value (Log)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same Industry*, *Crossborder*, *Poison*, *Tender*, *Multiple Bidders*, *Relative Size*, and *Bidder Size (Log)*. All other variables are defined as in Table 2. Detailed definitions are provided in the appendix. t-statistics based on standard errors clustered by the target's (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Sample:	Private Targets			
Dependent Variable:	Bidder CAR (in Percentage Points)			
Target Equity Beta	1.41***	1.64***	1.37***	2.16***
	(4.95)	(5.24)	(4.38)	(4.69)
Beta Spread (Equity)				-1.06**
				(-2.27)
Bidder SDC Industry × Year FE	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes
Target Controls	No	Yes	Yes	Yes
Bidder Controls	No	No	Yes	Yes
Observations	13,610	13,490	12,211	12,112

Table A.3: Non-Parametric Estimation of the Sensitivity of Bidder CAR to Target Asset Beta

This table presents OLS estimates of the sensitivity of the cumulative abnormal return of the bidder's stock during the seven-day window around the bid announcement (*Bidder CAR*) to the target's asset beta. The sample period is 1977 to 2015. Only bids for private targets are included. $\mathbb{1}\{a < \text{Target Asset Beta} \leq b\}$ is an indicator equal to one if the target's asset beta is larger than a but smaller than (or equal to) b. *Deal Controls* is a vector comprising all deal-level controls included in column (5) of Table 2: *Beta Spread*, *Deal Value (Log)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same Industry*, *Crossborder*, *Poison*, *Tender*, *Multiple Bidders*, *Relative Size*, and *Bidder Size (Log)*. All other variables are defined as in Table 2. Detailed definitions are provided in the appendix. t-statistics based on standard errors clustered by the target's (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)
Sample:	Private Targets
Dependent Variable: Bidder CAR (in Percentage Points)	
$\mathbb{1}\{-\infty < \text{Target Asset Beta} \leq 0.20\}$	-2.66***
	(-2.83)
$\mathbb{1}\{0.20 < \text{Target Asset Beta} \leq 0.32\}$	-1.67***
	(-2.87)
$\mathbb{1}\{0.32 < \text{Target Asset Beta} \leq 0.44\}$	-0.88*
	(-1.74)
$\mathbb{1}\{0.44 < \text{Target Asset Beta} \leq 0.56\}$	-0.58
	(-1.47)
$\mathbb{1}\{0.56 < \text{Target Asset Beta} \leq 0.68\}$	-0.30
	(-0.88)
$\mathbb{1}\{0.68 < \text{Target Asset Beta} \leq 0.80\}$	-0.13
	(-0.44)
$\mathbb{1}\{0.92 < \text{Target Asset Beta} \leq 1.04\}$	0.55*
	(1.68)
$\mathbb{1}\{1.04 < \text{Target Asset Beta} \leq 1.16\}$	0.39
	(1.00)
$\mathbb{1}\{1.16 < \text{Target Asset Beta} \leq 1.28\}$	1.21***
	(2.64)
$\mathbb{1}\{1.28 < \text{Target Asset Beta} \leq 1.40\}$	1.21***
	(2.66)
$\mathbb{1}\{1.40 < \text{Target Asset Beta} < \infty\}$	1.25***
	(2.84)
Bidder SDC Industry × Year FE	Yes
Deal Controls	Yes
Target Controls	Yes
Bidder Controls	Yes
Observations	12,109

Table A.4: Non-Parametric Estimation of the Sensitivity of Bidder CAR to Target Asset Beta: Private vs. Public Targets

This table presents OLS estimates of the sensitivity of the cumulative abnormal return of the bidder's stock during the seven-day window around the bid announcement (*Bidder CAR*) to the target's asset beta. The sample period is 1977 to 2015. $\mathbb{1}\{a < \text{Target Asset Beta} \leq b\}$ is an indicator equal to one if the target's asset beta is larger than a but smaller than (or equal to) b. *Deal Controls* is a vector comprising all deal-level controls included in column (5) of Table 2: *Beta Spread*, *Deal Value (Log)*, *Equity*, *Cash*, *Toehold*, *Hostile*, *Same Industry*, *Crossborder*, *Poison*, *Tender*, *Multiple Bidders*, *Relative Size*, and *Bidder Size (Log)*. All other variables are defined as in Table 2. Detailed definitions are provided in the appendix. t-statistics based on standard errors clustered by the target's (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)
Sample:	Private Targets	Public Targets
Dependent Variable:	Bidder CAR (in Percentage Points)	
$\mathbb{1}\{-\infty < \text{Target Asset Beta} \leq 0.25\}$	-2.25***	-1.75*
	(-4.19)	(-1.88)
$\mathbb{1}\{0.25 < \text{Target Asset Beta} \leq 0.48\}$	-1.16***	-1.74***
	(-3.27)	(-2.69)
$\mathbb{1}\{0.48 < \text{Target Asset Beta} \leq 0.71\}$	-0.50*	-0.52
	(-1.88)	(-0.94)
$\mathbb{1}\{0.94 < \text{Target Asset Beta} \leq 1.17\}$	0.54*	-0.72
	(1.91)	(-1.32)
$\mathbb{1}\{1.17 < \text{Target Asset Beta} \leq 1.40\}$	1.22***	0.00
	(3.53)	(0.00)
$\mathbb{1}\{1.40 < \text{Target Asset Beta} < \infty\}$	1.29***	-1.10
	(3.04)	(-0.89)
Bidder SDC Industry × Year FE	Yes	Yes
Deal Controls	Yes	Yes
Target Controls	Yes	Yes
Bidder Controls	Yes	Yes
Observations	12,109	3,894

Table A.5: Alternative Method of Payment Definitions

This table presents OLS estimates of the sensitivity of the propensity to offer different types of payment to the bidder's asset beta (*Bidder Asset Beta*). The sample period is 1977 to 2015. *Equity* is an indicator equal to one if the proposed payment includes stock. *Above 50% Stock* is an indicator equal to one if the proposed payment consists of more than 50% stock. *Stock vs. Cash* is an indicator equal to one if 100% of the proposed payment is in stock and zero if 100% of the proposed payment is in cash. Deals for which the proposed payment comprises both stock and cash are excluded from column (3). *Deal Controls* is a vector comprising all deal-level controls included in column (2) to (4) of Table 6: *Deal Value (Log)*, *Toehold*, *Hostile*, *Same Industry*, *Crossborder*, *Poison*, *Tender*, *Multiple Bidders*, *Relative Size*, and *Bidder Size (Log)*. All other variables are defined as in Table 6. Detailed definitions are provided in the appendix. t-statistics based on standard errors clustered by the bidder's (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)
Sample:	Private and Public Targets		
Dependent Variable:	Equity	Above 50% Stock	Stock vs. Cash
Bidder Asset Beta	10.18***	8.50***	10.78***
	(4.81)	(4.73)	(5.41)
Target Asset Beta	-0.19	-0.95	-0.86
	(-0.06)	(-0.31)	(-0.28)
Target SDC Industry × Year FE	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes
Target Controls	Yes	Yes	Yes
Bidder Controls	Yes	Yes	Yes
Observations	18,348	17,631	13,237

Table A.6: Method of Payment and Target Equity Beta

This table presents OLS estimates of the sensitivity of the propensity to offer an all-stock payment to the bidder's equity beta. The sample period is 1977 to 2015. *Bidder (Target) Equity Beta* are the bidder's and target's equity beta, respectively. *Deal Controls* is a vector comprising all deal-level controls included in columns (2) to (4) of Table 6: *Deal Value (Log)*, *Toehold*, *Hostile*, *Same Industry*, *Crossborder*, *Poison*, *Tender*, *Multiple Bidders*, *Relative Size*, and *Bidder Size (Log)*. All other variables are defined as in Table 6. Detailed definitions are provided in the appendix. t-statistics based on standard errors clustered by the bidder's (SIC3-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Sample:	Private and Public Targets			
Dependent Variable:	100% Stock			
Bidder Equity Beta	7.61***	7.62***	5.54***	5.52***
	(3.86)	(3.90)	(3.54)	(3.47)
Target Equity Beta				0.01
				(0.00)
Target SDC Industry × Year FE	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes
Target Controls	No	Yes	Yes	Yes
Bidder Controls	No	No	Yes	Yes
Observations	21,082	20,471	18,428	18,354

Table A.7: Descriptive Statistics – Public Firms in Compustat

This table presents descriptive statistics for all public firms in Compustat. The sample period is 1977 to 2015. All continuous variables are winsorized at the 1st and 99th percentile. Detailed definitions are provided in the appendix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	Public Firms in Compustat							
Variable:	Observations	Mean	SD	Min.	*p*25	*p*50	*p*75	Max.
Repurchase	401,784	0.23	0.42	0	0	0	0	1
SEO	401,397	0.52	0.50	0	0	1	1	1
Asset Beta	319,281	0.86	0.35	0.17	0.61	0.86	1.12	1.64
Market Capitalization (in $M)	323,369	1,346	4,726	0	18	88	477	35,739
Market Capitalization (Log)	323,277	4.57	2.44	-12.72	2.91	4.48	6.17	14.41
Market-to-Book	268,111	3.23	5.66	0.19	0.99	1.66	3.04	43.29
Cash to Assets	345,205	0.17	0.22	0.00	0.02	0.07	0.22	0.96
Debt to Assets	343,987	0.31	0.43	0.00	0.04	0.21	0.41	3.29
ROA	344,168	-0.19	0.88	-6.91	-0.06	0.02	0.06	0.32
Cash Flow to Assets	331,447	-0.15	0.89	-7.02	-0.03	0.05	0.11	0.39

Table A.8: Share Repurchases, Seasoned Equity Offerings, and Equity Beta

This table presents OLS estimates of the sensitivity of the propensity to repurchase shares (*Repurchase*) and to conduct seasoned equity offerings (*SEO*) to the firm's equity beta (*Equity Beta*). The sample period is 1977 to 2015. All public firms in Compustat are included. All variables are defined as in Table 7. Detailed definitions are provided in the appendix. t-statistics based on standard errors clustered by the firm's (SIC2-) industry are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Sample:	Public Firms in Compustat			
Dependent Variable:	Repurchase_t		SEO_t	
Equity Beta_{t-1}	-6.60**	-9.73***	15.50***	11.18***
	(-2.29)	(-6.08)	(5.07)	(6.41)
Market $\text{Capitalization}_{t-1}$ (Log)		4.85***		4.92***
		(21.53)		(18.35)
$\text{Market-to-Book}_{t-1}$		-0.44***		0.40***
		(-7.09)		(3.89)
Cash to Assets_{t-1}		-3.10		2.50
		(-0.90)		(0.92)
Debt to Assets_{t-1}		-9.94***		-4.68
		(-5.04)		(-1.48)
ROA_{t-1}		2.81		8.51**
		(0.82)		(2.18)
Cash Flow to Assets_{t-1}		3.90		-12.97***
		(1.11)		(-2.96)
SIC2 Industry × Year FE	Yes	Yes	Yes	Yes
Observations	333,001	219,584	332,629	219,260

Model Variation: Levered Target

Consider a levered target that maintains a constant interest coverage ratio. The bidder's valuation of the target's equity is

$$E_t = (1 + \kappa \times \tau) \times \frac{FCF_{t+1}}{r_f + \beta_A \times \mu - g} - D_t, \tag{A1}$$

where $\kappa \equiv \textit{Interest Expense}_t / FCF_t \geq 0$ denotes the (inverse of the) interest coverage ratio, τ the corporate income tax rate, and D_t the level of net debt in the target's current capital structure. The market's valuation of the target's equity is[40]

$$\widetilde{E}_t = (1 + \kappa \times \tau) \times \frac{FCF_{t+1}}{r_f + \mu - g} - D_t, \tag{A2}$$

and the bidder's cumulative abnormal return around the bid announcement is

$$CAR_t^{Bidder} = (1 + \kappa \times \tau) \times \frac{\rho \times \pi}{E_t^{Bidder}} \times \left(\frac{FCF_{t+1}}{r_f + \mu - g} - \frac{FCF_{t+1}}{r_f + \beta_A \times \mu - g} \right). \tag{A3}$$

Note that $(1 + \kappa \times \tau) \geq 1$ and $\partial \kappa / \partial \beta_A = \partial \tau / \partial \beta_A = 0$. Hence, all predictions derived in Section 2 for the case of an unlevered target remain qualitatively unchanged.

Model Variation: Sloped Empirical SML

Suppose the empirical SML has a slope of $\gamma \times \mu$ for some $\gamma \in [0, 1]$ and crosses the CAPM-implied SML at $\beta = 1$. In that case, the target's cost of capital implied by the empirical SML is

$$\widetilde{r}_A = r_f + (\gamma \times \beta_A + 1 - \gamma) \times \mu, \tag{A4}$$

and the market's assessment of the target's value is

$$\widetilde{E}_t = \frac{FCF_{t+1}}{r_f + (\gamma \times \beta_A + 1 - \gamma) \times \mu - g}. \tag{A5}$$

[40] We assume that there is no disagreement between the bidder and the market about the level of net debt (D_t) in the target's current capital structure.

The bidder's cumulative abnormal return around the bid announcement is

$$CAR_t^{Bidder} = \frac{\rho \times \pi}{E_t^{Bidder}} \times \left[\frac{FCF_{t+1}}{r_f + (\gamma \times \beta_A + 1 - \gamma) \times \mu - g} - \frac{FCF_{t+1}}{r_f + \beta_A \times \mu - g}\right] \tag{A6}$$

$$= \frac{R \times \rho \times \mu \times (1-\gamma) \times (\beta_A - 1)}{r_f + (\gamma \times \beta_A + 1 - \gamma) \times \mu - g} \text{ with } R \equiv \frac{B_t}{E_t^{Bidder}} = \frac{\pi \times E_t}{E_t^{Bidder}}. \tag{A7}$$

Hence, for $\gamma \in (0,1)$, we have[41]

$$\frac{\partial CAR_t^{Bidder}}{\partial \beta_A} = R \times \rho \times \mu \times \left[\frac{1}{r_f + \beta_A \times \mu - g} - \frac{\gamma \times (r_f + \beta_A \times \mu - g)}{[r_f + (\gamma \times \beta_A + 1 - \gamma) \times \mu - g]^2}\right], \tag{A8}$$

$$\frac{\partial^2 CAR_t^{Bidder}}{\partial \beta_A \partial R} = \rho \times \mu \times \left[\frac{1}{r_f + \beta_A \times \mu - g} - \frac{\gamma \times (r_f + \beta_A \times \mu - g)}{[r_f + (\gamma \times \beta_A + 1 - \gamma) \times \mu - g]^2}\right], \tag{A9}$$

$$\frac{\partial^2 CAR_t^{Bidder}}{\partial \beta_A \partial g} = \frac{\rho \times \pi \times \mu \times FCF_{t+1}}{E_t^{Bidder}} \times \left[\frac{2}{(r_f + \beta_A \times \mu - g)^3} - \frac{2\gamma}{[r_f + (\gamma \times \beta_A + 1 - \gamma) \times \mu - g]^3}\right], \tag{A10}$$

and

$$\frac{\partial CAR_t^{Bidder}}{\partial \beta_A} > 0 \iff \beta_A < 1 + \frac{r_f + \mu - g}{\mu \times \sqrt{\gamma}} \tag{A11}$$

$$\frac{\partial^2 CAR_t^{Bidder}}{\partial \beta_A \partial R} > 0 \iff \beta_A < 1 + \frac{r_f + \mu - g}{\mu \times \sqrt{\gamma}} \tag{A12}$$

$$\frac{\partial^2 CAR_t^{Bidder}}{\partial \beta_A \partial g} > 0 \iff \beta_A < 1 + \frac{r_f + \mu - g}{\mu \times \gamma^{\frac{1}{3}}}. \tag{A13}$$

[41] For $\gamma = 0$, the empirical SML is flat and all results are as in Section 2. For $\gamma = 1$, the empirical SML coincides with the SML implied by the CAPM, and $CAR_t^{Bidder} = 0$ for all β_A.

Construction of Hypothetical Mutual Fund Fire Sales (***HMFFS***)

The following description is based on Dessaint, Foucault, Frésard, and Matray (2018). For each stock i, we construct $HMFFS_{i,q,t}$, a measure of hypothetical sales of stock i in quarter q of year t due to large outflows in mutual funds owning the stock. Our approach follows the three-step approach proposed by Edmans, Goldstein, and Jiang (2012).

First, in each year t, we estimate quarterly mutual fund flows for all U.S. funds that are not specialized in a given industry using CRSP mutual funds data. For every fund, CRSP reports the monthly return and the total net assets (TNA) by asset class. The average return of fund j in month m of year t is given by

$$Return_{j,m,t} = \frac{\sum_k (TNA_{k,j,m,t} \times Return_{k,j,m,t})}{\sum_k TNA_{k,j,m,t}},$$

where k indexes asset classes. We compound monthly fund returns to estimate average quarterly returns and aggregate TNAs across asset classes in March, June, September, and December to obtain the TNA of fund j at the end of every quarter in each year.

An estimate of the net inflow experienced by fund j in quarter q of year t is then given by

$$Flow_{j,q,t} = \frac{TNA_{j,q,t} - TNA_{j,q-1,t} \times (1 + Return_{j,q,t})}{TNA_{j,q-1,t}},$$

where $TNA_{j,q,t}$ is the total net asset value of fund j at the end of quarter q in year t, and $Return_{j,q,t}$ is the return of fund j in quarter q of year t. $Flow_{j,q,t}$ is therefore the net inflow experienced by fund j in quarter q of year t as a percentage of its net asset value at the beginning of the quarter.

Second, we calculate the dollar value of fund's j holdings of stock i at the end of every quarter using data from CDA Spectrum/Thomson. CDA Spectrum/Thomson provides the number of stocks held by all U.S. funds at the end of every quarter. The total value of the participation held by fund's j in firm i at the end of quarter q in year t is

$$SHARES_{i,j,q,t} \times PRC_{i,q,t},$$

where $SHARES_{j,i,q,t}$ is the number of stocks i held by fund j at the end of quarter q in year t, and $PRC_{i,q,t}$ is the price of stock i at the end of quarter q in year t.

Finally, for all mutual funds for which $Flow_{j,q,t} \leq -0.05$, we compute

$$HMFFS_{i,q,t}^{dollars} = \sum_j (Flow_{j,q,t} \times SHARES_{j,i,q-1,t} \times PRC_{i,q-1,t}).$$

This variable corresponds to the hypothetical net selling of stock i, in dollars, by all mutual funds subject to extreme outflows (outflows greater or equal to 5%). We then normalize $HMFFS_{i,q,t}^{dollars}$ by the dollar volume of trading in stock i in quarter q of year t ($VOL_{i,q,t}$) and define

$$HMFFS_{i,q,t} \equiv \frac{\sum_j (Flow_{j,q,t} \times SHARES_{j,i,q-1,t} \times PRC_{i,q-1,t})}{VOL_{i,q,t}} = \frac{HMFFS_{i,q,t}^{dollars}}{VOL_{i,q,t}}.$$